Bank performance and corporate culture

Stentella Lopes, F.S.

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Francesco Saverio Stentella Lopes

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PROMOTORES:
Prof. dr. F. Fiordelisi
Prof. dr. L.D.R. Renneboog

OVERIGE LEDEN VAN DE PROMOTIECOMMISSIE:

Dr. F. Castiglionesi
Dr. O. G. De Jonghe
Dr. M. F. Penas
Dr. O.Ricci

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Introduction

This doctoral thesis focuses on two different topics: the impact of economic expectations on bank performance and corporate culture.

The first topic, the link between economic expectations and the performance of banks, has received little attention in the existing literature. This is surprising because Coval and Thakor (2005) show that the increased relevance of the banking systems in developed economies can be explained by heterogeneous beliefs among economic agents. Specifically, their model includes three types of agents: optimistic, pessimistic, and rational agents. Optimistic agents overestimate the success probability of any project; pessimistic agents generally underestimate it; and rational agents can correctly assess the probability of economic success. Coval and Thakor (2005) show that in an economy characterized by the above beliefs system, rational agents will become financial intermediaries, pessimistic agents will become investors, and optimistic agents will become entrepreneurs. The intuition behind this result is that rational agents can profitably finance optimistic entrepreneurs who cannot be funded by pessimistic investors. The model predicts that investors have generally different expectations than bankers about future economic outcomes and that banks will report better performance in periods of high economic optimism.

Chapter 1 of this thesis examines how bankers' expectations about future merger gains are reflected in the performance of the merged banks in the long run and in the investors' reaction to a deal's announcement. Specifically, I analyze whether expected cost-saving synergies are reflected in more positive investors' reactions and in higher long-run performance of the merged banks. The main finding of this paper is that investors are generally skeptical about bankers' projections. I show that the expected cost-saving synergies do not always increase investors' reactions to the deal announcement but are generally reflected in higher long-run performance of the merged banks. This paper is coauthored with Franco Fiordelisi and has been accepted for presentation in Cass Business School during the 4th edition of the "Emerging Scholars in Banking and Finance Conference."

Chapter 2 analyzes the impact of high expectations for future economic success (i.e., high optimism) on the profitability of banks. Specifically, this chapter analyzes the performance of the US banking systems in periods of high optimism. The main finding of this paper is that banks operating in more competitive environments report better performance in periods of high economic optimism. I show that in periods of high optimism, credit losses in banks' lending portfolios increase only in protected banking systems. I interpret these findings to mean that banks operating in competitive environments are able to measure credit risk more precisely and perform better in periods of high optimism.

The existing literature has shown that high expectations for future economic success are an important determinant of firms' propensity to undertake innovative projects (Galasso et al. 2011 and Hirshleifer et al. 2012). In the last chapter of this thesis, I shift my focus to the firms' innovation activity and its relation to corporate culture.

Chapter 3 analyzes whether a creativity-oriented corporate culture is positively associated with firms' innovation activity. I use the Competitive Value Framework to identify four different corporate cultures: creative, competitive, control-oriented, and collaborative. I use text analysis to estimate a score for each corporate culture. The main finding of this paper is that a creative corporate culture is positively associated with investment in R&D, with firms patenting activity, and with firm value. To alleviate endogeneity problems, I also instrument corporate culture with tax credit on R&D in the United States. The results from the instrumental variable approach confirm the positive association between a creative corporate culture and the firm's innovation activity. This paper is coauthored with Luc Renneboog, Franco Fiordelisi, and Ornella Ricci.

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Chapter 1:

Errare Humanum Est, Perseverare Autem Diabolicum: A Test of Investors learning from information spillover

Abstract: Prior research indicates that cost saving synergies disclosed by the buyer at a merger deal's announcement are not fully capitalized in the market prices of the banks involved in the merger (Houston et al., 2001). This is surprising because these synergies are generally achieved within three years of the merger announcement. We posit that investors discount buyer expectations of cost saving synergies because at the announcement date, they do not have enough information to correctly evaluate the long-run effect of the reorganization plan. Because some information relevant for pricing the merger could spill over from concluded deals (DeLong and De Young, 2007), we test whether the number of mergers concluded in the recent past moderates the link between investor reactions and expected cost saving synergies communicated at the announcement date. Our results indicate that the link between investor reactions and expected cost savings becomes gradually positive as merger activity becomes more intense. We also find that the expected cost saving synergies are positively related to the long-run performance of the merging banks. Therefore, in periods of intense merger activity, the link between investor reactions and expected cost savings is more consistent with the cost savings realized in the long-run performance of the merged banks. Our results overall suggest that investors use the information spilling over from concluded deals to price the merger announcement, and in periods of intense merger activity, their reactions become more consistent with the long-run performance of merging banks.

1. Introduction

In recent decades, the US banking industry has experienced intense merger activity. The number of banks has substantially declined, increasing industry concentration. The 10 largest banks in the United States went from controlling 13.5% of the industry assets in 1980 to controlling roughly half of the market by the end of 2010 (Adams, 2012). This consolidation followed in the wake of important regulatory reforms and technological advances that completely changed banking activity (De Young et al., 2009). Merging banks must reorganize, and how such reorganizations occur can have far-reaching effects on the long-run performance of merging banks.

Although some information about the reorganization plan of the banks involved in a merger is usually communicated, little is known about how investors react to this information. Only Houston et al. (2001) empirically examine the relation between bank reorganizations and value creation. They find that reorganization is an important source of value creation, because investors react positively to deals that are expected to generate cost-saving synergies in the long run. However, they also show that cost-saving expectations are not entirely capitalized in the market price of merging banks upon the merger announcement. This evidence is surprising because the authors show that the expected cost saving synergies are completely met by three years from the merger announcement. Moreover, analyzing press releases and financial reports, Houston et al. (2001) show that financial analysts are generally sceptical about the management projections of future synergies.

In a more recent study, De Long and De Young (2007) show that in periods of intense merger activity, investor reaction to deal announcements becomes more consistent with the long-run performance of the merged banks because information relevant for pricing the merger spills over from concluded deals. Specifically, the authors show that the number of deals concluded in the recent past substantially strengthens the positive link between investor reaction and the long-run performance of merged banks. These results indicate that in period of intense merger activity, investors are better able to identify deals that enhance the long-run performance of merged banks. Because cost-savings should positively affect the long-run performance of merged banks, the number of deals communicated in the recent past may also decrease investor scepticism. This may moderate the link between investor reactions and the cost savings the bidder expects to achieve through reorganization of the target. This evidence leads us to the following research question: Does the number of deals concluded in the recent past moderate the link between investor reactions and expected cost saving synergies?

To address this question, we use a sample of 167 mergers announced by US banks between 1999 and pre-crisis 2007. We collect information on the expected cost savings communicated at the deal announcement. These estimated synergies are the amount of cost savings the bidder expects to realize through expense reductions at the target.

We show that the link between investor reactions and the expected cost saving synergies becomes positive when merger activity becomes more intense. Although the two are not positively associated in periods of low merger activity, when the number of deals concluded in the recent past increases, the link between investor reactions and expected costs savings becomes positive. This finding suggests that an increase in the number of mergers announced in the recent past leads investors to adjust upward their expectations on the effect that the cost savings communicated at the announcement date will have on the long-run performance of the merged banks. Thus, some relevant information about the link between expected cost savings and long-run performance might spill over from concluded deals. An alternative explanation could be that investors’ expectations about future merger gains become overly optimistic in periods of intense merger activity (Rhodes-Kropf and Viswanathan, 2004; Rhodes-Kropf et al., 2005).

These two explanations lead to opposing predictions about the effect that expected cost savings would have on the long-run performance of merging banks. The increased investor knowledge explanation predicts that expected cost savings would have a positive effect on the long-run performance of merging banks. Conversely, if investors are overly optimistic in periods of intense merger activity, we would expect to see a negative or at least non-positive link between buyer expectations and long-run performance. To disentangle these two alternative explanations, we analyze the effect of expected cost saving synergies on the long-run performance of merged banks.

We find that higher expected cost saving synergies are positively associated with the long-run performance of the merged banks, including increased long-run profitability, enhanced interest margins, and improved cost efficiency. Hence, our results as a whole indicate that investor reaction to the expected synergies upon the announcement becomes more consistent with the effect that the expected cost saving synergies have on the long-run performance of the merged banks as merger activity becomes more intense.

The main contribution of this paper is that we offer the first empirical evidence that investor reaction to expected cost saving synergies significantly changes depending on the number of deals concluded in the recent past. Our empirical findings are consistent with Houston et al. (2001) in establishing that investors can react positively to restructuring plans that are expected to generate cost saving synergies in the long run, but we go further by showing that this positive relationship holds only in periods of intense merger activity. We show that an increase in the available information decreases investors scepticism about managers' projections. Our results indicate that investor scepticism about expected cost savings is mainly due to a lack of information needed to price the deal. When the information available to price the merger increases as a spillover from previous deals, the investor reaction becomes more positive. We also show that the expected cost saving synergies are positively associated with the long-run performance of merged banks. Hence, our results are also in line with those of De Long and De Young (2007) in showing that in periods of intense merger activity investor reactions to expected costs saving are more consistent with the effect that these expected synergies have on the long-run performance of merged banks.

The remainder of this paper is structured as follows. Section 2 outlines the relevant literature bank mergers and acquisitions as well as presenting our formal hypotheses. Section 3 describes our variables, data, and formal tests. Section 4 presents our empirical analysis. Sections 5 and 6 give an overview of our results in regard to our two hypotheses. Section 7 presents a robustness check. Section 8 concludes.

2. Related Studies and Hypotheses

Previous research shows that banks use mergers and acquisitions (M&As) to reorganize in response to technological and activity changes (Berger et al., 1999; Dymski, 1999; Group of Ten, 2001; Amel et al., 2004; Jones and Critchfield, 2005; De Young et al., 2009). Bank reorganization substantially affects the efficiency, profitability, and composition of lending portfolios. Specifically, Berger et al. (1998) outline how M&As affect the propensity of banks to lend to small borrowers. Sapienza (2002) shows that M&As increase both bank efficiency and banks' market power in setting loan rates. Hannan and Pilloff (2006) find that efficient banks tend to acquire their more inefficient counterparts, suggesting potential post-merger efficiency improvements. Similarly, Fraser and Zhang (2009) demonstrate that the profitability and efficiency of the target firm increases by three years after the deal announcement.

The literature indicates a general consensus that the reorganization process substantially influences future performance of merged banks. As such, the reorganization plan disclosed at the merger announcement is likely to affect investors' reactions to the deal. However, the effects of reorganization following the merger can take more than one year to be fully felt (Berger et al., 1998; Houston et al., 2001; Bonaccorsi di Patti and Gobbi, 2007; Fraser and Zhang, 2009), and investors may have difficulty determining at announcement whether banks are likely to meet expected future merger gains in the long run.

To the best of the authors' knowledge, only one paper (Houston et al., 2001) directly assesses the link between expected cost saving synergies and investors' reactions to deal announcements, and those authors find a positive link. However, Houston et al. (2001) also show that investors capitalize only half of the buyer's expectation of future cost saving synergies in the stock prices of the banks involved in the merger, indicating some degree of investor scepticism about the manager's projections. The authors show that this lower-than-expected market reaction, to some degree, comes from investor scepticism. Specifically, they argue that investors can react negatively to the disclosure of expected synergies if they believe the numbers are being used to justify a questionable deal. The investors' scepticism, however, is surprising because in Houston et al.'s sample, the bidders' estimates of future synergies are generally realized within three years of the deal announcement.

De Long and De Young (2007) document that investor reaction to a deal announcement is more consistent with the long-run performance of the merged banks if that deal is announced in periods of intense merger activity. They attribute this result to information relevant to the price of the merger spilling over from concluded deals. Therefore, although investors may be sceptical about the disclosed expected synergies in periods of restricted merger activity, when the number of deals concluded in the recent past increases, investor reaction becomes gradually positive. We argue that the number of deals concluded in the recent past moderates the investor reaction to the disclosure of expected cost saving. Specifically, our first hypothesis states

> H1: *The number of deals concluded in the recent past moderates the link between investor reactions to the merger announcement and expected cost saving.*

H1 suggests that investors use the information spilling over from concluded deals to adjust their reaction to expected cost savings disclosed by the bidder upon the announcement. However, an increase in merger activity can also be generated by overly optimistic expectations about future economic success (Rhodes-Kropf and Viswanathan, 2004; Rhodes-Kropf et al., 2005). Therefore, any change in the link between expected cost savings and investor reaction in periods of intense merger activity can also be triggered by investors having overly optimistic expectations about the merger's outcome. To disentangle these two alternative hypotheses, we test whether the higher expectations of future cost saving synergies are reflected in higher long-run performance of the merging banks. Our second research hypothesis is

> H2: *An increase in the cost saving synergies communicated at the announcement date increases the long-run performance of the merged banks.*

3. Data and Variables

We first define the criteria used to select our merger sample. Section 3.1 outlines how we calculate the market reaction to a portfolio composed of the target and the buyer stocks that we use to proxy for investor reaction to the deal announcement. Section 3.2 reports how we construct the long-run difference in performance of the merged banks, defined as the difference between the combined performance of the merging banks one year before the merger and the performance of the resulting banks three years after the merger announcement.

Merger deals are selected using the following six criteria: 1) the buyer is a commercial or savings bank 2) the acquirer buys the entire target company; 3) both the acquirer and the target company are listed banks operating in the United States, and stock prices are available on CRSP; 4) mergers were announced between 1999 and 2007; 5) the buyer’s accounting data one year before and three years after the merger announcement are available on the SNL database; and 6) accounting data of the target company one year before the merger announcement are available on the SNL database. The resulting sample includes stock and accounting data for the two entities involved in 167 mergers between 1999 and 2007. We end our sample period in 2007 to avoid distortions caused by the financial crisis of 2007–2009.

[Insert here Table 1]

Table 1 provides descriptive statistics on the merger sample. The table shows that 2000 is the year in our sample with the highest number of mergers, followed by 1999 and 2004. The average deal value in our sample is 891 $ Million, with the largest deal being the acquisition of Bank One by JP Morgan in 2004. However, the year with the highest average deal value in our sample is 2003, when we observe two large deals: the acquisition of Fleet Bank by Bank of America and the acquisition of First Virginia Bank by BB&T.

Our focus variable is the expected cost saving synergies generated by expense reductions at the target firm, as estimated by the bidder. The cost savings are disclosed as a percentage of the target's expenses and arise from closing target branches, selling underperforming assets, or generally downsizing the target. These expected synergies are higher than 0 for roughly half of our sample (85 mergers) and range from 7% to the 60% of the target expenses. Following De Long and De Young (2007), for each deal i, we allow investors to learn from observing the public information spilling over from concluded deals. We construct three learning variables. The first, $lbyo_i^1$, counts the number of deals announced by any banks in the last 365 calendar days before the deal's announcement. The other two variables, $lbyo_i^2$ and $lbyo_i^3$, count, respectively, the number of deals announced in the previous 730 and 1095 calendar days before the announcement of the i-th deal in the sample. To distinguish the information spillover from the effect of a bank's merger experience, we include the control variable *learning by doing*. We construct three different learning by doing variables that count the number of deals announced by the same bank in the previous 365, 730, or 1095 calendar days. We also control for the target's weight based on the total assets of the entity resulting from the merger. For each deal, we construct three proxies for the level of diversification achieved through the merger. The first two variables concern geographical diversification: the variable $partial\ overlap_i$ takes a value of 1 if some of the target bank's and bidder's offices or branches are located in different counties. The second variable for geographical diversification, $no\ overlap_i$, takes a value of 1 if all buyer and target bank offices and branches are located in different counties, and 0 otherwise. The *activity diversification* variable is a dummy that takes a value of 1 if the correlation between the target company and the acquirer's stock is below the sample median, and 0 otherwise. We also control for the method of payment, constructing a dummy that takes a value of 1 if the majority of the consideration was paid in shares, and 0 otherwise. We add a count variable ($state_{it}$) for the number of deals that occurred in the same year in the US state in which the target bank of deal i has its headquarters. This variable aims to control for potential geographical drivers of merger activity such as regulation differences. We also add a dummy variable for the accounting method used by the buyer to record the deal; it takes a value 1 if the acquisition is considered a purchase, which allows banks to amortize the difference between the target company's market value and the acquisition value. Finally, we also add a dummy named "equals," which is 1 if the deal was announced as a "merger of equals" and 0 otherwise. The information about the mergers is collected from SNL, and we matched the M&A and the firms' databases using CUSIP codes. Table 2 describes all these variables and Table 3 reports some descriptive statistics.

[Insert here Table 2 and 3]

Table 3 reports the percentiles of the focus variables. Of particular importance to our analysis, Table 3 shows that the mean of the variable *learning by observing* calculated over the last 365 calendar days is 1.78 with a standard deviation of 3.88. Table 3 also reports the percentile values. For example, the 25th percentile value for the variable *learning by observing* calculated over 365 days is 1.45 and the median value is 1.74. Similarly, the table reports the summary statistics and the percentile values for all the learning variables. Table 3 also shows that the variable *expected costs saving* has a mean of 14.35 and a standard deviation of 15.86.

[Insert here Table 4]

Table 4 reports descriptive statistics for the variables used in the estimation as controls. The target represents, on average, 16.95% of the entity resulting from the merger. $Partial\ overlap_i$ is a dummy variable taking a value of 1 if the target and the buyer have some branches or offices in the different US county, and 0 otherwise. This variable has a mean of 0.21. The variable $no\ overlap_i$ takes the value of 1 when all the branches of the target are located in a county where the bidder has no branches, and 0 otherwise. This variable has a mean of 0.43. In our sample, roughly 2.39% of the mergers are announced as mergers between equals. Moreover, in 47.30% of the analyzed deals, the majority of the consideration was paid in stocks, and 77.24% of the deals were recorded as purchases.

3.1 Investor Valuation

We use an event study methodology to proxy the investor reaction upon the merger announcement. Specifically, we run the following market model using ordinary least squares (OLS) for each firm involved in a merger in our dataset:

$$R_{it} = a_i + b_i R_{mt} + \zeta_{it} \qquad (1)$$

R_{mt} is the daily return of the NASDAQ bank index, i = (1,167) indexes the mergers, and t (-252, -20) indexes the days prior to the merger announcement. R_{it} is either the daily return of the acquiring bank R^A_{it}, the market return of the target's stock R^T_{it}, or the return of the combined market value of both financial firms R^C_{it} calculated as:

$$R^C_{it} = ln[(MV^A_{it} + MV^T_{it})/(MV^A_{it-1} + MV^T_{it-1})]. \qquad (2)$$

MV_{it}^{A} is the market value of the acquiring bank at day t, and MV_{it}^{T} is the market value of the target company at day t. Finally, we calculate the cumulative abnormal return (CAR) for three different time windows starting 10 or five days before the acquisition and ending at T= 1,5 days after the announcement.

$$CAR_{it} = \sum_{t=-k}^{T} R_{it} - (\hat{a}_i + \hat{b}_i R_{mt}) \qquad (3)$$

From equation (3), we then obtain three different CARs (-5,5), (-10,5), and (-10,1),[1] which are reported in Table 5. Because our focus is on the expected synergies generated by the merger, we next turn to the abnormal returns on the combined portfolio $R_{i,t}^{C}$.

[Insert here table 5]

The CARs reported in Table 5 show that the announcement of banking mergers, on average, destroys acquiring banks' shareholder wealth, whereas the shareholders of the target earn strong positive abnormal returns. In addition, the deal announcement does not have a statistically significant effect on the portfolio of the target and buyer stocks.

3.2 Long-run Merger Gains

We define long-run merger gains as the difference between the combined performance of the merging banks one year before the merger announcement and the

[1] For the portfolio of the combined target and buyer stocks, we also test whether investors anticipated the merger, discounting part of the deal effect before the announcement. Specifically, for the combined portfolio, we calculate the abnormal return on the windows (-40, -1) and (-20,-1) and find no evidence of an anticipation effect: neither of the abnormal returns is statistically distinguishable from zero.

performance of the resulting bank three years after the merger. This time gap is consistent with the literature (Berger et al., 1998; Houston et al., 2001; De Long and De Young, 2007), which shows that the full effect of the merger only becomes clear three years after its announcement.

We address three types of gains: profits, interest margin[2], and cost efficiency. Following De Long and De Young (2007), we use accounting ratios from before and after the deal. Specifically, we use the return on assets (ROA) to measure profits, the ratio of net interest income to total assets to measure the interest margin, and the ratio of non-interest expenses to operating income to measure cost efficiency.

Because we restrict our sample to deals in which the entire target company was acquired, we can construct a combined performance (CP_{it}) for each deal (i) announced in year (t), weighting the stand-alone performances of the acquiring bank (P_t^A) and the target company (P_t^T) on their relevance in terms of weight (Total Assets) in the resulting firm:

$$CP_{it} = P_{it}^A \frac{TA_{it}^A}{TA_{it}^A + TA_{it}^T} + P_{it}^T \frac{TA_{it}^T}{TA_{it}^A + TA_{it}^T} . \qquad (4)$$

Finally, we construct our proxy for actual generated merger gains for the *i-th* bank at time *t* by subtracting the combined performance one year before the deal from the realised performance (P_{it}^A) of the resulting bank three years after the merger announcement:

$$Merger\ gains_{it} = P_{it+3}^A - CP_{it-1} . \qquad (5)$$

[2] While the effect of expected cost saving on profitability and on cost efficiency appears to be clear, higher cost efficiency may also increase the interest revenues. This would reduce the bank's marginal costs and lead to an increase in the banks market shares and as a result to a larger interest margin.

P_{it} stands for ROA, interest margin, and cost efficiency. Table 6 reports summary statistics for all actual synergies resulting from equation (5).

[Insert here table 6]

Table 6 indicates how the long performance of merged banks differs during periods of intense merger activity. Specifically, the long-run difference in profitability (ROA) is negative (-0.0077) in periods of low merger activity but becomes slightly positive (0.0008) when merger activity becomes more intense. The same dynamic is also apparent in the difference in the interest margin, which becomes less negative in periods of intense merger activity, and in regard to cost efficiency, even though the mean in periods of intense merger activity is not significant. This evidence is consistent with De Long and De Young (2007), suggesting that managers tend to perform better in periods of intense merger activity. We then test whether the investors consider the management estimates more reliable in periods of intense merger activity.

4. Empirical Framework

We test our first hypothesis using the following equation:

$$CAR_{ijt} = \alpha + \lambda_1 \mathrm{E}(cs)_{ijt} + \lambda_2 Learning\ by\ Observing_{ijt} + \lambda_3 Learning\ by\ Observing_{ijt} * \mathrm{E}(cs)_{ijt} + \theta Controls_{ijt} + \gamma_{jt} + \omega_{ijt} \quad (6)$$

We estimate equation (6) using industry-year fixed effects. The dependent variable (CAR_{ijt}) is the CAR[3] of deal i announced in year t, where the buyer has the

[3] We implicitly assume that the estimation error in the CAR calculation is not correlated with the independent variables used in the paper. Therefore, equation 6 can be consistently estimated using a least squares technique.

SIC code j. The coefficient on the interaction between the variable *learning by observing* and the estimated cost saving synergies λ_3 is our test for H1, which posits that the number of deals concluded in the recent past moderates the link between investor reaction and the expected cost saving synergies.

To test our second hypothesis, we use as the dependent variable $Merger\ gains$ and use the following equation:

$$Merger\ gains_{ijt} = \alpha + \beta_1\,\mathrm{E}(cs)_{ijt} + \beta_2 Learning\ by\ Observing_{ijt} + \theta Controls_{ijt} + \gamma_{jt} + \varepsilon_{ijt}\,.\ (7)$$

We estimate equation (7) using industry-year fixed effects. $Merger\ gains_{ijt}$ is the difference between the combined performance of the target and the bidder one year before the deal and the performance of the bank resulting from the merger three years after the deal. The coefficient on the expected cost saving synergies β_1 is our test for our second hypothesis (H2), which holds that the expected cost saving synergies positively affect the long-run performance of the bank resulting from the merger.

5 Investor Reaction and the Expected Cost Saving Synergies

Table 7 reports the estimation of equation 6 using industry-year fixed effects. We use as a dependent variable the CARs calculated on three different event widows:

(-5,5), (-10,5), and (-10,1) and three different measure for our learning variables that we calculate on a time horizon of: 365 calendar days ($lbyo_i^1$ and $lbydo_i^1$), 730 days ($lbyo_i^2$ and $lbydo_i^2$) and 1095 ($lbyo_i^3$ and $lbydo_i^3$) calendar days.

[Insert here Table 7]

Our results confirm hypothesis H1: the link between investor reaction and expected costs saving synergies is substantially moderated by the number of deals concluded in the recent past. The coefficient on the interaction between the expected cost saving synergies and our variable learning by observing ($lbyo_i^k$), which is our test for H1, is positive and statistically significant (p<0.10), irrespective of the time horizon used to calculate the learning variables or the event window used to calculate the CARs. In only one event window (5,5) the interaction is not statistically significant if we calculate the learning by observing variable on a time horizon of two calendar years (730 days). However, using the other two learning variables, calculated respectively on 365 and on 730 calendar days, the interaction between the variable learning by observing and the expected cost savings becomes positive and statistically significant (p<0.10) even in the window (-5,5). The results outlined in Table 7 show that the moderation effect of the variable learning by observing on the link between expected cost savings and CARs is more statistically significant if we use a time horizon of 365 calendar days to calculate the learning variables. This evidence suggests that investors assign more weight to more recent deals.[4]

We now turn our attention to the first three models, where we use learning variables calculated on a time horizon of 365 calendar days. The estimated coefficient on the interaction between the variable learning by observing and expected cost

[4] To understand whether investors assign more weight to more recent information, we also calculate two weighted learning by observing variables: $\mathrm{lbyo}_i^{\mathrm{old}}$ and $\mathrm{lbyo}_i^{\mathrm{recent}}$. The variable $\mathrm{lbyo}_i^{\mathrm{old}}$ is constructed by assigning more weight to older deals, and the variable $\mathrm{lbyo}_i^{\mathrm{recent}}$ is constructed by assigning more weight to deals closer in time to the announcement of the i-th deal. The unreported results confirm the evidence in Table 7 that investors assign more weight to more recent information. These results are available upon request.

saving is 0.00116 ($p<0.10$) in Model 1, which uses the event window (-5,5); 0.00184 ($p<0.05$) in Model 2, which uses the event window (-10,5); and 0.00202 ($p<0.01$) in Model 3, which uses the event window (-10,1).

We find that the number of deals concluded in the recent past moderates the link between investor reaction and expected cost saving synergies by weakening the negative effect of announced cost saving on CARs. Moreover, this moderation effect is strong enough to change the sign of the relation. Specifically, in Model 2 the link between expected cost savings and the investor reaction is negative if the variable learning by doing is below the relevant threshold of 1.93, which falls into approximately the 75th percentile of the learning variable. However, when the learning variable increases above 1.93, the link between cost savings and investor reaction becomes positive. As an example, when few deals have been communicated in the recent past and the variable learning by observing lies in its 25th percentile (1.45), a one standard deviation increase in the expected cost saving synergies (15.86) decreases the CAR by an economically meaningful 1.41%. This effect is highly statistically significant ($p<0.01$). However, when merger activity becomes more intense and the variable learning by observing assumes a value in its 75th percentile (1.98), this negative effect disappears. A one standard deviation increase in the expected cost saving synergies would then increase investor reaction in the event window (-10,5) by 0.13%. This effect, however, is not statistically significant given that the value of the variable learning by observing is very close to the switching point. However, Table 7 shows that this effect becomes gradually more positive and statistically significant when the learning variable increases above the 75th percentile, approaching the tail of the distribution. This evidence is consistent with H1 in indicating that the number of deals concluded in the recent past substantially moderates the link between expected cost savings and investor reaction to the deal announcement. Our evidence suggests that the information spilling over from deals announced in the recent past leads investors to adjust upward their reactions to the bidder's expected cost saving synergies.

Our results also show that the announcement of deals that involve larger banks tend to generate lower abnormal returns. The natural logarithm of the buyer's total assets has a negative and significant ($p<0.10$) effect in all the models reported in Table 7.

6. Merger Gains and Expected Cost Saving Synergies

Table 8 reports the estimation of Equation 7 using industry-year fixed effects. Our dependent variable is the merger gains calculated as described in Section 3.2. Specifically, we present three types of merger gains: profits, interest margin, and efficiency gains, which are calculated as the long-run difference in ROA, interest margin, and cost efficiency (non-interest expenses to operating income), respectively.

[Insert here Table 8]

Our results in Table 8 confirm hypothesis H2, which posits that an increase in the expected cost saving synergies increases the long-run performance of the merged banks. The coefficient on the expected cost savings is positive and statistically significant ($p<0.1$) in all of the models that use the ROA or the interest margin as a dependent variable. Specifically, in Models 1 and 3 the link between the expected cost saving synergies and the long-run difference in performance is 0.00010 ($p<0.05$) for the long-run difference in ROA and 0.00005 ($p<0.1$) for the long-run difference in the interest margin. A one standard deviation (15.885) increase in the expected cost saving synergies generates an increase in the long-run difference in ROA of 0.16%. Using the average acquiring bank ROA one year before the deal announcement (1.26%) as a benchmark, this represents an increase of 12.59%. We find that the interest margin has a similar effect: a one standard deviation increase in the expected cost saving synergies generates a 0.08% increase in the long-run difference in the interest margin. Using the average acquiring firm interest margin one year before the deal announcement (3.67%) as a benchmark, this represents a 2.16% increase.

Table 8 also reports qualitatively similar results when we look at the long-run differences in cost efficiency. Specifically, the coefficient estimated in Model 2, which uses the long-run difference in efficiency as a dependent variable, is negative and statistically significant ($p<0.10$) at -0.00122. Thus, a one standard deviation increase in expected cost saving synergies, on average, decreases the ratio of non-interest expenses to operating income by 1.93%. Using the average acquiring bank efficiency ratio (57.78%) one year before the deal as a benchmark, this translates into a decrease of 2.47%.

Our results show that an increase in the expected cost saving synergies communicated at the announcement date is positively associated with the long-run performance of the merging banks. A one standard deviation increase in the expected cost saving synergies generates an improvement in all of the analyzed long-run differences in accounting performance. The variable *learning by observing* does not have a statistically significant effect on the long-run performance of merging banks in our sample, irrespective of the time horizon used to calculate the learning variable.[5] *Learning by doing* is positively associated with the long-run difference in the interest margin when we calculate the learning variable on a time horizon of one year. However, this relation is not statistically significant when we use a greater number of days to calculate the variable.

7. Robustness Check

In the previous section, we analyzed how the number of deals concluded in the recent past substantially moderates the link between investor reaction and the acquiring bank's estimation of cost saving synergies. This relationship is positive only in periods of high merger activity. The negative relationship in periods of low merger activity could stem from investors believing that the announced cost savings estimates are being used by the acquiring bank to justify a questionable deal.

In this section, we use Heckman's (1979) two-step selection model to test whether the acquiring bank's decision to communicate cost savings synergies higher than zero is based on unobserved characteristics of the banks involved in the deal that are negatively correlated with the investor reaction upon the deal announcement. The two-step model requires strong distributional assumptions, and therefore the results reported in Table 9 have to be considered with caution.

To use the selection model, we collapse the expectation of cost saving synergies into a dummy variable taking a value of one if the expected synergies disclosed at the announcement date are higher than zero. In the first step, we run a probit model using the cost-savings dummy as the dependent variable and the same independent variable as used in the main analysis. We then augment equation (6) with

[5] We also test whether the number of deals concluded in the recent past moderates the link between merger gains and expected cost saving synergies. Because the estimated coefficients are not statistically distinguishable from zero, we do not report these results.

an inverse Mills ratio calculated with the parameters estimated in the first stage.

We use a measure of barriers to out-of-the-state entry as an instrument to determine the likelihood that the buyer expects to achieve cost saving synergies higher than zero. As outlined in Rice and Strahan (2010), the 1994 Interstate Banking and Branching Efficiency Act (IBBEA) allowed nationwide branching, but it also permitted states to limit out-of-the-state entries. These entry barriers fall into four categories: 1) states can decide a minimum age of the target before it can be acquired by out-of-state banks; 2) states can also opt to forbid new interstate branching; 3) each state can decide whether to allow entry through the acquisition of a single branch or part of a target institution; and 4) the states can also impose a statewide deposit cap on branch acquisitions. The branch restriction index changes across time and states. After the approval of IBBEA in 1994, all but 13 states imposed a minimum age for the target in an interstate acquisition. Moreover, the majority of states (36) did not opt-in for *de novo* entry. Entry through the acquisition of only one branch or part of an institution was also forbidden in 30 states after passage of IBBEA, and 35 states imposed a cap of 30% or higher on the amount of deposits in the state that can be held or controlled by any single bank or bank holding after an interstate acquisition that constitutes an initial entry. As discussed by Rice and Strahan (2010), an attempt to eliminate these branch restrictions was made in 2006. However, the attempt did not succeed and the entry barriers limited the acquisition from out-of-the-state banks in our sample period from 1999 to 2007. These barriers may impede efficient banks from acquiring their less efficient peers, limiting the expected cost saving achievable through the acquisition.

[Insert here Table 9]

Table 9 reports the results estimated using the selection model. Model (1) reports the results from the probit estimation used to calculate the inverse Mills ratio. As anticipated, the link between the branch restriction index and the expected cost savings dummy is negative and highly statistically significant (p<0.01), indicating that the branch restrictions hindered efficient banks from acquiring less efficient target companies. The coefficient on the inverse Mills ratio is our test for selection on unobservable factors. Models (2), (3), and (4) show that the coefficient on the inverse Mills ratio is not statistically distinguishable from 0 in all models. Thus, we have no evidence of selection on unobserved characteristics of the merging banks. Moreover, the moderation effect of the number of concluded deals in the recent past ($lbyo_{ijt}^{1}$) on the link between the expected cost savings dummy and the investor reaction to the announcement is still positive and significant (p<0.1) in all of the event windows. Therefore, the selection model confirms the results reported in the main analysis that as the number of deals concluded in the recent past increases, so too does the investor reaction to estimated cost savings.

8. Conclusion

Recent decades have seen intense merger activity in the US banking industry. This consolidation, principally brought on by reorganization following important regulatory and technological changes, has completely transformed banking activity. The reorganization of the banks involved in such mergers then assumes great relevance. Often upon the deal announcement, the bidder bank discloses its expectations about expected cost savings from reorganization of the target. The extant literature shows that upon the announcement of the merger, investors do not fully capitalize on the market prices of the banks involved in the deal the estimated cost saving disclosed by the buyer (Houston et al. 2001). This is surprising because research shows that the buyer expectations are generally met within three years of the merger (Houston et al. 2001). A possible explanation for this result is that investors, at the announcement date, discount part of the expected synergies because they do not have enough information to accurately evaluate the long-run effect of the reorganization plan. De Long and De Young (2007) show that investors use the information spilling over from deals concluded in the recent past to price the merger announcement. We examine whether the number of deals concluded in the recent past moderates the link between cost saving synergies disclosed at the announcement date and investor reactions. We use a sample of 167 acquisitions announced by US banks between 1999 and 2007, and collect information on expected cost saving synergies communicated at the deal announcements. We find that the number of deals concluded in the recent past substantially moderates the link between investors' reactions and expected cost saving synergies communicated at the announcement date. We show that the moderation effect is strong enough to invert the sign of the association between investors' reactions and cost saving synergies. Stock market participants seem to interpret the disclosure of expected cost savings as a justification for questionable deals in periods of low merger activity, when the link between investor reaction and expected synergies is negative. However, when the number of deals increases, this link becomes positive.

We also test whether the expected cost savings at the announcement date are systematically correlated with unobserved characteristics of the deal that negatively affect investor reaction, but we do not find clear evidence to support this idea.

Finally, we show that the cost saving synergies communicated at the announcement date are positively associated with the long-run performance of merging banks. Hence, during periods of intense merger activity, investor reactions to expected cost savings become more consistent with the effect that these expected synergies have on the long-run performance of merged banks. This evidence is consistent with De Long and De Young (2007) in suggesting that information relevant to pricing the merger spills over from concluded deals.

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Table 1: The merger sample

Percentile	Number of merger	Average size of the buyer: Total Assets (Mil)	Average size of the buyer: Total Assets (Mil)	Average deal value (Mil)
1999	29	33,900	951	500
2000	30	41,900	1,283	548
2001	17	27,900	4,443	592
2002	11	33,300	2,588	128
2003	18	69,300	920	2,760
2004	23	39,700	1,084	2,384
2005	8	17,500	2,801	349
2006	11	40,600	786	388
2007	20	63,200	3,071	366
Observation	167	167	167	167

Table 2: Variables description

Variable name	Abbreviation	Description	Source
Expected cost saving (%)	$E(cs)_{it}$	The percentage of expense reductions at the target, as estimated by the bidder	SNL M&A
Target relative dimension	$\frac{TA_{it-1}^{T}}{TA_{it-1}^{A}+TA_{it-1}^{T}}$	The ratio of the assets of the target the year before the deal to the total assets of both banks involved in the merger one year before the merger	SNL
Learning by observing	$lbyo_{it}^{k}$	The number of deals announced by any banks in the recent past before the announcement of deal i. We construct three learning variables:(1) $lbyo_{i}^{1}$, for the number of deals communicated by any bank in the previous 365 calendar days; (2) a variable counting the number of deals communicated in the previous 730 calendar days ($lbyo_{i}^{2}$); and (3) a variable counting the number of deals communicated in the previous 1095 calendar days ($lbyo_{i}^{3}$).	SNL M&A
Learning by doing	$lbydo_{it}^{k}$	The number of all deals announced by the same bank in the recent past, before the announcement of deal i. We construct three variable: (1) $lbydo_{i}^{1}$, counting the number of deals announced by the same bank in the previous 365 calendar days; (2) $lbydo_{i}^{2}$, counting the number of deals announced by the same bank in the previous 730 calendar days; and (3) $lbydo_{i}^{3}$, counting the number of deals communicated by the same bank in the previous 1095 calendar days.	SNL M&A
Geographical diversification (1)	$partial\ overlap_{it}$	A dummy variable taking a value of 1 if the target company and acquirer offices are partly located in different counties.	
Geographical diversification (2)	$no\ overlap_{it}$	A dummy variable taking a value of 1 if all the target branches and offices are located in different US counties.	SNL M&A
Activity diversification	$act\ div_{it}$	A dummy variable taking a value of 1 if the correlation between the acquirer and target company stock is below the sample median, and 0 otherwise	CRSP
Merger between equals	$equals_{it}$	A dummy variable taking a value of 1 if the merger was announced as a “merger of equals,” and 0 otherwise	SNL M&A

Accounting method used to incorporate the target company	$method_{it}$	Post-merger accounting ratios can change if the acquirer bank uses the pooling method versus the purchase method to incorporate the target company into its books (De Long, 2003). $method_i$is a dummy variable equal to 1 for mergers that use the purchase method and 0 otherwise.	SNL M&A
Payment method	$stockpay_{it}$	A dummy variable taking a value of 1 if the majority of the consideration was paid in stock, 0 otherwise	SNL M&A
Dimension of the acquiring bank	$\log(TA)_{it}$	The natural logarithm of the acquiring bank total asset	SNL M&A
Difference in capitalization of the bank resulting from the merger (%)	$\Delta(\frac{E}{TA})_{it}$	The difference between the target company and acquirer combined leverage (eq.2), one year before and the leverage of the bank resulting from the deal three years after the deal's announcement.	SNL firms
Number of deals occurred in the state of the buyer	$state_{it}$	The number of deals that occurred in the same US state where the acquiring bank of deal i has its headquarter	SNL firms
Average market reaction to recent deals	$Hot\ market_{it}$	The average investor reaction (cumulative abnormal return) of the last 5 deals before the announcement	CRSP
Branch restriction index	$branch\ restrictioni\ index_{it}$	The regulatory restrictions to out-of-the state entries in the state in which the Target is located	Rice and Strahan (2010)

Table 3: Summary Statistics of the main variables

percentile	Learning-by-observing 365 days (hundreds)	Learning-by-observing 730 days (hundreds)	Learning-by-observing 1095 days (hundreds)	Learning-by-doing 365 days (units)	Learning-by-doing 730 days (units)	Learning-by-doing 1095 days (units)	Expected cost saving (%)
Mean	1.78	3.88	6.27	1.06	2.05	3.05	14.35
Standard deviation	0.41	1.30	2.09	1.91	2.89	3.91	15.86
1	1.17	2.51	4	0	0	0	0
25	1.45	2.94	4.38	0	0	0	0
50	1.74	3.42	5.06	0	1	2	10
75	1.98	4.17	8.47	1	3	4	25
99	3.32	6.84	9.84	9	11	14	55
Observation	167	167	167	167	167	167	167

Table 4: Descriptive statistics

	mean	Standard deviation	max	min
Target relative dimension $(\frac{TA^T_{it-1}}{TA^A_{it-1}+TA^T_{it-1}})$	0.1695	0.2434	0.02	0.9765
Partial overlapping $(partial\ overlap_{it})$	0.2155	0.4124	0	1
No overlap $(no\ overlap_{it})$	0.4371	0.4975	0	1
Activity diversification $(act\ div_{it})$	0.5149	0.5012	0	1
Merger between equals $(equals_{it})$	0.0239	0.1533	0	1
Accounting method used to incorporate the target $(method_{it})$	0.7724	0.4205	0	1
Payment method $(stockpay_{it})$	0.4730	0.5077	0	1
Size of the acquiring bank $(\log(TA)_{it})$	15.9984	1.8591	11.1711	20.2610
Difference in Capitalization of the bank resulting from the merger $(\Delta(\frac{E}{TA})_{it})$	0.0749	0.3026	-0.7512	2.9719
Number of deals occurred in the state of the buyer $(state_{it})$	5.3353	4.2420	1	21
Average market reaction to the five most recent deals $(Hot\ market_{it})$	-0.0272	0.0429	-0.2073	0.05760
Branch restriction index $(branch\ restrictioni\ index_{it})$	1.6587	1.4260	0	4
Observations	167	167	167	167

Table 5: Summary statistics of Cumulative Abnormal Returns

This table reports the average cumulative abnormal returns. The Z-statistic reported in parentheses is adjusted for cross-sectional correlation, following the procedure suggested by Kolari and Pynnönen (2010) and used by Amici et al (2013).

Event Window	Target	Buyer	Combined
(-5,5)	20.07%***	-2.49%***	0.50%
	(14.1306)	(-5.1184)	(0.7993)
(-10, 5)	21.96%***	-2.48%***	0.51%
	(15.5531)	(-4.1470)	(0.9070)
(-10, 1)	21.67%***	-2.48%***	0.39%
	(15.4934)	(-5.4588)	(0.8842)
N	167	167	167

*** p<0.01, ** p<0.05, * p<0.1

Table 6:Summary statistics of created synergies

This table presents the results for the realized merger gain calculated as the difference between the performances of the buyer three years after the deal (P^A_{t+3}) and the weighted average of the buyer's and target's performance one year before the deal.

$$Merger\ gains_{it} = P^A_{it+3} - \left(P^A_{it-1}\frac{TA^A_{it-1}}{TA^A_{it-1} + TA^T_{it-1}} + P^T_{t-1}\frac{TA^T_{it-1}}{TA^A_{it-1} + TA^T_{it-1}}\right)$$

The table presents the results from the above equation substituting P^A and P^T, respectively, with the buyer and the target return on asset (ROA_{it}), net interest income on total asset ($Interest\ Income_{it}$), and the ratio of non-interest expenses to operating income ($efficiency_{it}$). Low merger activity refers to merger with the variable lbyo_{it} below the sample median, while high merger activity refers to deals with the variable lbyo_{it} above the sample median.

	Sample mean	Low merger activity	High merger activity
$\Delta(ROA)_{it}$	-0.0035***	-0.0077***	0.0008*
	(0.0007)	(0.0011)	(0.0004)
$\Delta(Interest\ Income)_{it}$	-0.0034***	-0.0043***	-0.0027***
	(0.0003)	(0.0005)	(0.0005)
$\Delta(Efficiency)_{it}$	0.0422***	0.0899***	-0.0099
	(0.0127)	(0.0022)	(0.0095)
Observations	167	167	167

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Market reaction on combined CARs

This table reports the estimation of the following model using time-industry dummies:

$$CAR_{ijt} = \alpha + \lambda_1 \,\mathrm{E}(cs)_{ijt} + \lambda_2 Learning\ by\ Observing_{ijt} + \lambda_3 Learning\ by\ Observing_{ijt} * \mathrm{E}(cs)_{ijt} + \theta Controls_{ijt} + \gamma_{jt} + \omega_{ijt}$$

The standard errors reported in parentheses are robust to heteroscedasticity.

	Learning variables 365 days			Learning variables 730 days			Learning variables 1095 days		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Car -5,5	Car -10,5	Car -10,1	Car -5,5	Car -10,5	Car -10,1	Car -5,5	Car -10,5	Car -10,1
$E(cs)_{ijt}$	-0.00249**	-0.00356**	-0.00398***	-0.00147*	-0.00187**	-0.00203**	-0.00189**	-0.00214**	-0.00191**
	(0.00118)	(0.00137)	(0.00111)	(0.00078)	(0.00094)	(0.00079)	(0.00085)	(0.00095)	(0.00082)
$lbyo_{ijt}^{k}$	-0.01030	-0.01496	-0.04052	0.00781	0.00296	-0.01211	0.00938	0.00328	-0.01149
	(0.02520)	(0.03155)	(0.02485)	(0.01511)	(0.01758)	(0.01476)	(0.01339)	(0.01614)	(0.01248)
$E(cs)_{ijt} * lbyo_{ijt}^{k}$	0.00116*	0.00184**	0.00202***	0.00027	0.00041*	0.00043**	0.00023*	0.00030*	0.00026**
	(0.00064)	(0.00077)	(0.00062)	(0.00017)	(0.00024)	(0.00019)	(0.00013)	(0.00015)	(0.00013)
$lbydo_{ijt}^{k}$	0.00116	0.00192	0.00332	0.00303	0.00181	0.00071	0.00113	0.00009	-0.00047
	(0.00322)	(0.00335)	(0.00295)	(0.00241)	(0.00246)	(0.00231)	(0.00180)	(0.00187)	(0.00159)
$\frac{TA_{ijt-1}^{T}}{TA_{ijt-1}^{A} + TA_{ijt-1}^{T}}$	-0.01522	0.02823	0.03220	-0.01520	0.02658	0.03108	-0.01599	0.02555	0.03089
	(0.02590)	(0.02958)	(0.02806)	(0.02523)	(0.02904)	(0.02791)	(0.02548)	(0.02930)	(0.02816)
$act\ div_{ijt}$	-0.00798	-0.00493	-0.00259	-0.00922	-0.00595	-0.00355	-0.00928	-0.00620	-0.00310
	(0.00943)	(0.01047)	(0.00857)	(0.00937)	(0.01048)	(0.00879)	(0.00965)	(0.01055)	(0.00904)
$partial\ overlap_{ijt}$	0.00301	0.00525	0.01152	0.00287	0.00657	0.01439	0.00358	0.00770	0.01499
	(0.01263)	(0.01314)	(0.01104)	(0.01221)	(0.01312)	(0.01125)	(0.01246)	(0.01297)	(0.01138)
$no\ overlap_{ijt}$	0.00093	0.00385	0.00695	0.00191	0.00488	0.00748	0.00260	0.00583	0.00768
	(0.01156)	(0.01159)	(0.01060)	(0.01142)	(0.01161)	(0.01049)	(0.01135)	(0.01167)	(0.01049)
$equals_{ijt}$	0.00376	0.01169	0.00116	0.00796	0.01447	0.00084	0.00256	0.01206	0.00554
	(0.02579)	(0.04126)	(0.02821)	(0.02580)	(0.04131)	(0.02954)	(0.02579)	(0.04114)	(0.03128)
$method_{ijt}$	-0.00007	0.01095	0.00988	-0.00003	0.01263	0.01410	-0.00035	0.01294	0.01467
	(0.01748)	(0.01805)	(0.01456)	(0.01641)	(0.01779)	(0.01554)	(0.01649)	(0.01764)	(0.01552)
$stockpay_{ijt}$	-0.00798	-0.01798	-0.00765	-0.00940	-0.01750	-0.00512	-0.00818	-0.01563	-0.00336
	(0.01165)	(0.01301)	(0.01140)	(0.01231)	(0.01367)	(0.01183)	(0.01227)	(0.01357)	(0.01183)
$log(TA)_{ijt}$	-0.00852*	-0.00836*	-0.00811**	-0.01028**	-0.00931*	-0.00795**	-0.00966**	-0.00871*	-0.00741**
	(0.00455)	(0.00481)	(0.00379)	(0.00457)	(0.00472)	(0.00373)	(0.00447)	(0.00467)	(0.00368)
$state_{ijt}$	0.00114	0.00110	0.00089	0.00150	0.00114	0.00061	0.00118	0.00082	0.00042
	(0.00114)	(0.00121)	(0.00107)	(0.00114)	(0.00129)	(0.00115)	(0.00112)	(0.00126)	(0.00108)
$\Delta(\frac{E}{TA})_{ijt}$	0.01365	0.01210	-0.00010	0.01241	0.01270	0.00227	0.01337	0.01249	-0.00053
	(0.01669)	(0.01648)	(0.01147)	(0.01561)	(0.01616)	(0.01149)	(0.01475)	(0.01532)	(0.01128)
$Hot\ market_{ijt}$	0.08418	0.08369	0.09565	0.07328	0.08207	0.09954	0.08361	0.09283	0.10409
	(0.10395)	(0.11817)	(0.10198)	(0.10853)	(0.11851)	(0.10200)	(0.10688)	(0.11739)	(0.10220)
$Constant$	0.12982	0.12229	0.17900**	0.07667	0.08334	0.16323	0.03407	0.06917	0.19398
	(0.09186)	(0.09917)	(0.08523)	(0.10895)	(0.12099)	(0.10503)	(0.13527)	(0.15896)	(0.12666)
$Observations$	167	167	167	167	167	167	167	167	167
$Time - SIC\ dummies$	Y	Y	Y	Y	Y	Y	Y	Y	Y
Switching point	2.1466	1.9348	1.9703	5.4444	4.5610	4.7209	8.2174	7.1333	7.3462
	$\frac{\Delta CAR}{\partial E(cs)}$ Evaluated at different level of $lbyo_{ijt}^{k}$								
$lbyo = 1pc$	-0.1133%**	-0.1407%***	-0.1617%***	-0.0792%**	-0.0841%**	-0.0951%***	-0.0970%***	-0.0940%**	-0.0870%**

$lbyo = 25pc$	-0.0808%**	-0.0892%***	-0.1051%***	-0.0676%**	-0.0665%**	-0.0766%**	-0.0883%***	-0.0826%**	-0.0771%**
$lbyo = 50pc$	-0.0472%**	-0.0358%**	-0.0465%**	-0.0547%**	-0.0468%*	-0.0559%**	-0.0726%**	-0.0622%**	-0.0594%**
$lbyo = 75pc$	-0.0193%	0.0083%	0.0020%	-0.0344%	-0.0160%	-0.0237%	0.0058%	0.0401%	0.0292%
$lbyo = 99pc$	0.1361%*	0.2549%**	0.2726%***	0.0377%	0.0934%	0.0911%*	0.0373%	0.0812%	0.0648%

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Regression on post-merger performance

This table reports the coefficients estimated using time-industry dummies when estimating the model below. We use the long-run difference in ROA, $(\Delta(ROA)_i)$, the long-run difference in the interest margin $(\Delta(Interest\ Margin)_i)$, and the long-run difference in the non-interest expenses to operating income ratio $(\Delta(efficiency)_i)$ as a proxy for $Merger\ Gains_{it}$.

$$Merger\ Gains_{ijt} = \alpha + \beta_1 E(cs)_{ijt} + \beta_2 Learning\ by\ Observing_{ijt} + \theta Controls_{ijt} + \gamma_{jt} + \varepsilon_{ijt}$$

The standard errors, reported in parentheses are robust to heteroscedasticity..

	Learning variables 365 days			Learning variables 730 days			Learning variables 1095 days		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	ROA	COST EFFIC.	INT. INC.	ROA	COST EFFIC.	INT. INC.	ROA	COST EFFIC.	INT. INC.
$E(cs)_{ijt}$	0.00010**	-0.00122*	0.00005*	0.00010**	-0.00126*	0.00005*	0.00011***	-0.00130*	0.00006**
	(0.00004)	(0.00071)	(0.00003)	(0.00004)	(0.00072)	(0.00003)	(0.00004)	(0.00074)	(0.00003)
$lbyo^k_{ijt}$	-0.00084	0.03206	-0.00078	-0.00119	0.01235	-0.00112	-0.00103	0.00558	-0.00140
	(0.00252)	(0.04910)	(0.00211)	(0.00137)	(0.02512)	(0.00129)	(0.00118)	(0.02529)	(0.00118)
$lbydo^k_{ijt}$	-0.00015	0.00138	0.00058**	-0.00027	0.00504	-0.00002	-0.00021	0.00312	-0.00011
	(0.00032)	(0.00579)	(0.00024)	(0.00027)	(0.00472)	(0.00019)	(0.00018)	(0.00319)	(0.00013)
$\frac{TA^T_{ijt-1}}{TA^A_{ijt-1}+TA^T_{ijt-1}}$	-0.00250	0.09432	-0.00202	-0.00272	0.09335	-0.00177	-0.00267	0.09190	-0.00178
	(0.00443)	(0.08357)	(0.00326)	(0.00439)	(0.08337)	(0.00326)	(0.00439)	(0.08360)	(0.00323)
$act\ div_{ijt}$	0.00087	-0.03142	-0.00056	0.00091	-0.03130	-0.00047	0.00080	-0.02902	-0.00046
	(0.00123)	(0.02620)	(0.00094)	(0.00122)	(0.02598)	(0.00098)	(0.00121)	(0.02551)	(0.00097)
$partial\ overlap_{ijt}$	-0.00131	0.03558	-0.00089	-0.00119	0.03404	-0.00072	-0.00123	0.03438	-0.00075
	(0.00209)	(0.04203)	(0.00107)	(0.00207)	(0.04154)	(0.00110)	(0.00207)	(0.04187)	(0.00109)
$no\ overlap_{ijt}$	0.00124	-0.02484	0.00083	0.00123	-0.02304	0.00071	0.00121	-0.02323	0.00063
	(0.00145)	(0.02636)	(0.00097)	(0.00144)	(0.02640)	(0.00100)	(0.00143)	(0.02637)	(0.00100)
$equals_{ijt}$	0.00070	0.06222	-0.00249	0.00025	0.07098	-0.00253	0.00071	0.06699	-0.00210
	(0.00292)	(0.06445)	(0.00322)	(0.00277)	(0.06335)	(0.00327)	(0.00276)	(0.06412)	(0.00314)
$method_{ijt}$	-0.00042	0.01700	0.00007	-0.00035	0.01625	0.00055	-0.00030	0.01624	0.00064
	(0.00164)	(0.03838)	(0.00178)	(0.00167)	(0.03844)	(0.00176)	(0.00165)	(0.03796)	(0.00175)
$stockpay_{ijt}$	-0.00028	0.01860	0.00002	-0.00005	0.01514	0.00025	-0.00001	0.01563	0.00040
	(0.00166)	(0.03145)	(0.00115)	(0.00161)	(0.03071)	(0.00118)	(0.00165)	(0.03143)	(0.00118)
$log(TA)_{ijt}$	0.00016	0.00497	-0.00011	0.00024	0.00254	0.00017	0.00025	0.00305	0.00025
	(0.00044)	(0.00792)	(0.00035)	(0.00045)	(0.00802)	(0.00035)	(0.00042)	(0.00737)	(0.00036)
$state_{ijt}$	0.00001	0.00059	-0.00016	-0.00003	0.00115	-0.00020*	-0.00001	0.00076	-0.00021**
	(0.00012)	(0.00237)	(0.00010)	(0.00013)	(0.00252)	(0.00011)	(0.00012)	(0.00230)	(0.00010)
$\Delta(\frac{E}{TA})_{ijt}$	-0.00262	0.01685	-0.00165	-0.00243	0.01260	-0.00144	-0.00252	0.01299	-0.00153
	(0.00191)	(0.03332)	(0.00128)	(0.00180)	(0.03239)	(0.00131)	(0.00180)	(0.03320)	(0.00127)
$Hot\ market_{ijt}$	0.03104	-0.45312	0.00619	0.03181*	-0.46579	0.00807	0.03186*	-0.46338	0.00861
	(0.01879)	(0.33528)	(0.01280)	(0.01873)	(0.33301)	(0.01332)	(0.01850)	(0.33004)	(0.01344)
$Constant$	0.00017	-0.17907	-0.00249	0.00495	-0.15654	-0.00033	0.00695	-0.13416	0.00478
	(0.00885)	(0.16801)	(0.00770)	(0.01052)	(0.20063)	(0.00957)	(0.01308)	(0.28017)	(0.01187)
$Observations$	167	167	167	167	167	167	167	167	167
$Time - SIC\ dummies$	Y	Y	Y	Y	Y	Y	Y	Y	Y

*** p<0.01, ** p<0.05, * p<0.1

Table 9: Selection model on CARs

This table reports the estimation of a two-step selection model. In the first step, we estimate a probit model using as the dependent variable a dummy taking a value of one if $E(cs)_{i,}$ the expected communicated cost saving synergies, are higher than 0. In the second step, we estimate the following regression using industry and time dummies:

$$CAR_{ijt} = \alpha + \delta_1 \mathbf{1}(cs)_{ijt} + \delta_2 Learning\ by\ Observing_{ijt} + \delta_3 Learning\ by\ Observing_{ijt} * \mathbf{1}(cs)_i\ + \delta_4\ Mills_{ijt} + \theta Controls_{ijt} + \gamma_{jt} + \xi_{ijt}.$$

The variable $Mills_{it}$ is the Mills ratio calculated using the parameters estimated in the first stage . The standard errors reported in parentheses are robust to heteroscedasticity.

	(1)	(2)	(3)	(4)
	$\mathbf{1}(cs)_{ijt}$	Car -5,5	Car -10,5	Car -10,1
$branch\ restrictioni\ index_i$	-0.28879***			
	(0.08882)			
$\mathbf{1}(cs)_{ijt}$		-0.00253**	-0.00361***	-0.00408***
		(0.00118)	(0.00138)	(0.00110)
$lbyo^1_{ijt}$	0.71279	-0.00655	-0.00837	-0.03375
	(0.64054)	(0.02385)	(0.03083)	(0.02555)
$lbydo^1_{ijt}$	0.03232	0.00052	0.00146	0.00337
	(0.07910)	(0.00314)	(0.00319)	(0.00282)
$\mathbf{1}(cs)_{ijt} * lbyo_{ijt}$		0.00115*	0.00179**	0.00198***
		(0.00063)	(0.00078)	(0.00063)
$\frac{TA^T_{ijt-1}}{TA^A_{ijt-1}+TA^T_{ijt-1}}$	-0.04148	-0.00381	0.04052	0.04322
	(0.82421)	(0.02653)	(0.03012)	(0.02662)
$act\ div_{ijt}$	-0.84932***	-0.00928	-0.00728	-0.00570
	(0.25182)	(0.00964)	(0.01079)	(0.00877)
$partial\ overlap_{ijt}$	0.58032	-0.00165	0.00076	0.00798
	(0.36836)	(0.01219)	(0.01278)	(0.01100)
$no\ overlap_{ijt}$	-0.34071	0.00031	0.00165	0.00370
	(0.28811)	(0.01121)	(0.01099)	(0.01012)
$equals_{ijt}$	-1.00060	0.00499	0.00786	-0.00536
	(0.68603)	(0.02801)	(0.04435)	(0.03101)
$method_{ijt}$	-0.25980	0.00438	0.01542	0.01242
	(0.39741)	(0.01696)	(0.01763)	(0.01462)
$stockpay_{ijt}$	-0.34438	-0.01282	-0.02236*	-0.01013
	(0.33884)	(0.01121)	(0.01273)	(0.01161)
$log(TA)_{ijt}$	0.12490	-0.00598	-0.00589	-0.00650*
	(0.10577)	(0.00421)	(0.00437)	(0.00358)
$state_{ijt}$	0.01913	0.00156	0.00150	0.00118
	(0.03056)	(0.00108)	(0.00115)	(0.00105)
$\Delta(\frac{E}{TA})_{ijt}$	0.37657	0.01690	0.01711	0.00441
	(0.46560)	(0.01708)	(0.01665)	(0.01135)
$Hot\ market_{ijt}$	1.01676	0.09175	0.09638	0.10149
	(2.87816)	(0.09776)	(0.10899)	(0.09456)
$Mills_{ijt}$		0.00438	0.00851	0.00874
		(0.00617)	(0.00700)	(0.00655)
$Constant$	-2.67078	0.08342	0.07257	0.14244*

	(2.34129)	(0.08919)	(0.09719)	(0.08561)
$Observation$	152	152	152	152
$Time\ SIC\ dummies$	Y	Y	Y	Y
Switching point		2.200	2.017	2.060

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Chapter 2: Optimism, bank performance, and banking competition

Abstract: a common assumption in the academic literature and in banking supervision is that competition decreases the profitability of banks. However, recent literature suggests that competition affects the profitability of banks in two opposing ways: it decreases interest revenues by lowering the banks' market power in setting rates on loans but also incentivizes banks to improve their technology to assess credit risk, decreasing the average loan losses in bank lending portfolios. In periods of credit expansion, such as periods of high expectation for future economic success (i.e. high optimism), the ability of banks to assess credit risk may be particularly valuable. I examine whether economic optimism moderates the relationship between banking competition and bank performance in the United States. I use the entry barriers erected by states to limit out-of-state entry after the approval of the Interstate Banking and Branching Efficiency Act to measure changes in competition that are not correlated with bank characteristics. I use two different measures for the level of optimism in the economy: the Consumer Sentiment Index calculated by the University of Michigan and a measure based on the exercising of options by CEOs in companies listed on the NYSE. I find that the level of optimism in the economy decreases the positive relation between entry barriers and bank profitability. In periods of high optimism and after the introduction of entry barriers, credit losses increase in protected banking systems, negatively affecting bank profitability.

1 Introduction

A standard principle in banking supervision is that competition decreases banks' profits (Jiménez et al. 2013). In line with this principle, recent empirical evidence (Rice and Strahan 2010) shows that banking competition reduces the market power of banks in setting loan rates, decreasing the average lending rate. The reduction in the average lending rate, however, can be associated with a decrease in the borrower default probability (Boyd and De Nicolò, 2005), which, in turn, can positively affect banks' profits. Existing empirical evidence shows that the relaxation of regulatory restrictions on banking competition in the United States substantially decreased credit losses in banks' lending portfolios (Jayaratne and Strahan, 1996 and 1998; Dick and Lehnert, 2010). Researchers argue that competition generates an incentive for banks to adopt more sophisticated technology to measure credit risk. These technologies allow banks to assess credit risk more precisely and, consequently, the credit quality of banks' lending portfolios in competitive banking systems improves. Therefore, banking competition has two contemporaneous effects on bank profitability: on the one hand, it weakens banks' market power in setting loan rates, negatively affecting bank profitability. On the other hand, competition improves banks' technological ability to assess credit risk and decreases credit losses, which has a positive effect on bank profitability. These opposing forces driving bank performance make the link between bank profitability and banking competition ambiguous. To shed more light on this relationship, it is important to understand the variables that moderate this link and cause the credit losses effect to prevail over the market power effect.

In spite of an extensive literature on banking competition (Black and Strahan, 2002; Cetorelli and Strahan, 2006; Kerr and Nanda, 2009), no papers have analyzed whether high expectations for future economic success or, more briefly, high economic optimism, influence the relation between banking competition and bank performance. This is surprising since high economic optimism may naturally lead to credit expansion, affecting both interest revenues from loans and credit losses. Specifically, high expectations for future economic success may decrease the expected default rate among borrowers, increasing the credit supply. Prior research has shown that banks in more competitive banking systems develop sophisticated technologies to measure credit risk. These technologies improve the banks' ability to assess credit risk and might be particularly valuable in periods of credit expansion, such as periods of high economic optimism. A natural question then arises: Does optimism moderate the effect of competition on the profitability of banks? I find that economic optimism does indeed influence the effect of competition on the profitability of banks. In periods of low optimism, competition decreases bank profitability, lowering a bank's market power. However, an increase in the level of optimism in the economy weakens the negative effect of competition on bank performance. I show that an increase in the level of optimism in the economy is associated with an increase in credit losses in protected banking systems. However, in banking systems fully open to competition, an increase in economic optimism does not increase credit losses. When the level of optimism in the economy is high (the optimism measure is in its 75th percentile), the increase in credit losses in protected credit markets is strong enough to cancel out the positive effect of market power on bank profitability. Overall, my results show that banks operating in more competitive environments are more able to identify credit risk in periods of high optimism. Moreover, my results indicate that as the level of optimism in the economy increases, the positive effect of market power on bank profitability vanishes.

A key problem in analyzing the effect of optimism on the relationship between banking competition and bank performance is finding a measure for competition that is not connected to bank characteristics. Following Rice and Strahan (2010), I use entry barriers erected by states after the approval of the Interstate Banking and Branching Efficiency Act (IBBEA) in 1994. Specifically, as outlined in Johnson and Rice (2008), IBBEA leaves to the states the power to limit banking competition, giving them the ability to erect four types of barriers to out-of-state entries. Because states repeatedly changed these entry barriers between 1994 and 2005, I use the entry barrier changes to approximate exogenous shocks to banking competition, exploiting their unique ability to generate changes in loan supply without affecting the credit demand (Rice and Strahan, 2010). I then investigate whether the level of optimism in the economy moderates the relationship between banking competition and bank performance. As a measure of the level of optimism in the economy, I use the Consumer Sentiment Index (CSI), an indicator designed to measure the degree of optimism in the US economy that is updated monthly by the University of Michigan. As a robustness check, I also calculate a second measure for the level of optimism in the economy, the percentage of CEOs (of firms listed on the New York Stock Exchange (NYSE)) who do not exercise stock options that are more than 67%[6] in the money for each year of my sample. This indicator is based on the assumption that CEOs do not exercise such stock options if they have high expectations about future economic success (Malmendier and Tate, 2008). I use both measures of optimism at the (census) regional level. Then, I interact the level of optimism with the regulatory entry barriers to test whether economic confidence moderates the effect of regulatory entry barriers on bank performance.

To the author's knowledge, this is the first paper to empirically analyze how optimism moderates the link between competition and bank performance. My findings are consistent with the theoretical results of Ruckes (2004) in showing that improving economic conditions significantly interact with banking competition in setting the quality of banks' lending portfolios. The effect of this interaction is particularly important because lowering the quality of banks' lending portfolios in periods of economic growth can engender a financial crisis when the economy takes a downturn (Dell'Ariccia and Márquez, 2006). My evidence is also consistent with the prediction of the Coval and Thakor (2005) model, which shows that banks can profit

[6] This threshold is consistent with the financial economic literature on optimism (e.g., Malmendier and Tate, 2008).

from a high level of optimism in the economy by funding optimistic borrowers that would not otherwise be financed by investors. Specifically, the authors outline that the dimension and the importance of the banking system in an economy is positively associated with the level of optimism as long as banks can correctly evaluate the borrower's default probability. In their framework, when optimism increases, the probability that an entrepreneur gets financed by investors decreases since investors are generally pessimist about the future outcome of the entrepreneur's project. As long as banks can correctly evaluate default probability of optimistic borrowers, they can profitably finance them. Therefore, banking systems increase in importance and in dimension when the level of optimism in the economy increases. This outcome is consistent with my evidence, which shows that banks with more sophisticated technology to assess credit risk perform better in periods of high economic optimism.

The remainder of this paper proceeds as follows. Section 2 provides some background on bank liberalization and describes the proxy for regulatory entry barriers. Section 3 discusses the literature and formulates the hypotheses. Section 4 describes the sample, the measure of optimism in the economy and the exogeneity of regulatory entry barriers. Section 5 introduces the empirical strategy, and Section 6 presents and discusses the results. Section 7 presents some robustness checks, and Section 8 concludes.

2 US credit market liberalization and branch restriction

I exploit differences in regulatory barriers to interstate branching in order to approximate exogenous shocks to banking competition. This section briefly reviews the recent history of US credit liberalization. In the 1970s, the large majority of states were enforcing restrictions on interstate branching. Between 1970 and 1994, 38 states eased their restrictions on branching. Kroszner and Strahan (1999) demonstrate that the mechanics behind this state-level deregulation mirrored the political leverage of lobbies in the financial services sector. States that were under the thumb of well-capitalized large banks were likely to remove branching limitations early on.

The 1994 Interstate Banking and Branching Efficiency Act (IBBEA) was the beginning of the full interstate banking system. Although IBBEA permitted nationwide branching, it gave states enough flexibility to govern its implementation. They were allowed to set measures to discourage entry. These obstacles to entry fell into four categories: 1) states were allowed to set a minimum age of the target institution before it could be acquired by out-of-state bank holdings; 2) IBBEA left the option to forbid new interstate branching; 3) each state can decide whether it would allow entry through the acquisition of a single branch or part of a target institution; and 4) each state can impose statewide deposit caps on branch acquisitions.

IBBEA left each state free to adopt a minimum age requirement for acquisition. Specifically, each state could decide how long an institution was required to have been operating in the state before it could become the target of an interstate acquisition. However, the states could not set a minimum age provision of more than five years. For example, if a newly installed subsidiary office were established in a state with a minimum age provision of three years, a bank holding company that would like to consolidate the office to a branch would have to postpone the acquisition until the subsidiary had met the minimum age requirement of three years.

IBBEA also states that *de novo* interstate branching is allowed only if a state explicitly “opts in.” Hence, a bank is allowed to establish a new interstate branch if the legislation of a given state unequivocally says so. Permitting *de novo* branching substantially increases credit market competition by leaving banks free to locate their branches in more profitable markets. Therefore, disallowing this *de novo* branching requirement is equivalent to erecting an entry barrier, because an out-of-state bank could then only enter another state's market via an interstate whole-bank merger. Moreover, the IBBEA also gives states the ability to prevent out-of-state entry through the acquisition of a branch (or a number of branches). Again, IBBEA says that states have to explicitly opt-in to allow the possibility of entry by the acquisition of a single branch or a number of branches.

The final entry barrier that can be erected in accordance with the IBBEA is a 30% limit on deposit concentration at a state level with regard to mergers that constitute the initial entry of a bank into a state. The act sets a ceiling of 30% on the amount of deposits in the state that can be held or controlled by any single bank or bank holding after an interstate acquisition that constitutes an initial entry. However, IBBEA also establishes that a state may loosen the concentration limitation to above 30% or set a deposit limit on an interstate bank merger transaction below 30%. The effect of this kind of measure is to discourage a bank from engaging in a larger interstate merger in the state.

Table 1 gives a timeline of U.S. credit market liberalization and places my sample period in context.

<<INSERT TABLE 1 HERE>>

3 Literature review and hypotheses

The relationship among banking competition, bank risk, and bank performance has been widely discussed in the banking research.[7] Various theoretical models (Marcus, 1984; Keeley, 1990) show that competition decreases bank charter values and worsens risk-taking incentives. Boyd and De Nicolò (2005) indicate that banking competition can also have the opposite effect of decreasing the risk in bank lending portfolios. The authors predict a negative relation between banking competition and the losses in bank lending portfolios. However, they also predict a decrease in bank revenues generated by higher banking competition; therefore, the relation between banking competition and bank performance remains ambiguous. Moreover, extensions of the Boyd and De Nicolò model allowing for imperfect correlation in loan defaults (Martinez-Miera and Repullo, 2010; Hakenes and Schnabel, 2011) show how banking competition can either increase or decrease bank risk, depending on other factors and the intensity of competition.

Hence, from a theoretical standpoint, the link between banking competition and bank performance can be either positive or negative, depending on the average lending rate and the ability of banks to assess credit risk. Various papers have tried to empirically test the relationship among banking competition, bank performance, and risk taking using different proxies for banking competition. The change in market contestability arising from banking liberalization has been widely used in the literature as a measure of competition. Jayaratne and Strahan (1996) document that the liberalization of the US credit market boosted economic growth. The authors argue that economic growth arises from the improved lending technologies of banks, which enhance their ability to assess credit risk. Black and Strahan (2002), Cetorelli and Strahan (2006), and Kerr and Nanda (2009) find that banking competition generates a substantial increase in credit supply, allowing previously excluded

7 See Degryse and Ongena (2008) for an extensive literature review.

borrowers to enter the credit market. Dick and Lehnert (2010) show that the increase in loan supply generated by credit market liberalization was also associated with lower losses in bank lending portfolios, indicating that bank lending technology improved after the credit market liberalization. Since the banks report profit net of the losses on their lending portfolios, credit liberalization may have a direct positive effect on bank profitability. However, banking competition also decreases the market power of banks in setting loan rates (Rice and Strahan, 2010), which decreases bank revenues. The final effect on profitability is, therefore, not clear. Specifically, Jayaratne and Strahan (1998) show that banking competition has two contemporaneous effects on bank profitability. On the one hand, it decreases bank revenues and bank market power in setting loan rates. On the other hand, competition reinforces the selection process among banks, leading those with better screening ability to increase their market shares. This selection process improves the quality of banks’ lending portfolios and decreases credit losses, such that the final effect on profitability is unclear.

The existing empirical evidence then shows how the effect of competition on bank profitability crucially depends on credit supply and on the composition of banks’ lending portfolios. However, various theoretical papers argue that the composition of banks’ lending portfolios tend to deteriorate in periods of high economic success. Ruckes (2004) shows that improving economic conditions can lead to lax screening: the proportion of creditworthy borrowers increases in economic boom periods, making costly screening less desirable. Importantly, Ruckes calls attention to the valuable role of competition in keeping the quality of banks’ lending portfolios high in periods of economic growth. Dell’Ariccia and Márquez (2006) report a similar result, showing that the increase in credit demand in periods of economic growth can lead banks to lower their lending standards in an attempt to acquire market shares. The authors also find that upswings in the economy can interact with competition in defining the composition of banks' lending portfolios.

Upswings in the business cycle, generally anticipated by high expectations about future economic success (Beaudry and Portier 2006), can then interact with competition in defining the credit quality in banks' lending portfolios. Allen and Saunders (2002) show that the borrower screening errors made by banks substantially correlate with the business cycle, since banks tend to underestimate borrowers' default probabilities in periods of improving economic conditions. I posit that this phenomenon is more significant in protected banking systems. Therefore, in banking systems protected by geographical restriction to competition, I expect credit losses to be positively associated with economic optimism. Since competition incentivizes banks to develop sophisticated technology to assess borrowers' credit quality, in competitive environments banks may be able to precisely measure credit risk, even in periods of high optimism.

H1. As the level of optimism increases, the credit losses in banks' lending portfolios in protected banking systems also increase.

H1 states that in less competitive credit markets where regulatory restrictions to banking competition are higher, high economic optimism causes the losses in banks' lending portfolios to increase. Because banks disclose their profit net of credit losses, this phenomenon has an immediate negative effect on bank profitability. Therefore, even if regulatory restrictions to competition provide banks with some market power in setting loan rates that increases bank profitability, I expect the positive effect of entry barriers on banks profits to decrease in periods of high optimism.

H2. As the level of optimism in the economy increases, the positive relation between regulatory entry barriers and bank profitability decreases.

4 Data and Variables for the Empirical Design

I combine data from the Federal Reserve Bank of Chicago's commercial bank database with the state-level branching restriction index. The Federal Reserve database contains information on all commercial and savings banks that are regulated by the Federal Reserve System. I use reports of commercial banks from 1993 (i.e., the year before IBBEA passed) to 2006 (i.e., the year after the last documented change in regulatory entry barriers). Hence, the sample of banks contains reports from 1993 to 2006, with a total of 105,073 observations.

4.1 The branch restriction index

The branch restriction index comes from Johnson and Rice (2008) and is reported in Table 2. According to Rice and Strahan (2010), the index is set to 4 for all states before the first change in regulatory restrictions. Table 2 shows that the index changes at least once in all states during my sample period, and more than once for 15 states. After the approval of IBBEA in 1994, all but 13 states imposed a minimum age for the target of an interstate acquisition, with an average minimum age of 4.7 years. Moreover, the majority of states (36) did not opt-in for *de novo* entry. Entry through the acquisition of only one branch or part of an institution was also forbidden in 30 states after passage of IBBEA, and 35 states imposed a cap of 30% or higher on the amount of deposits in the state that can be held or controlled by any single bank or bank holding after an interstate acquisition that constitutes an initial entry.

<< INSERT HERE TABLE 2>>

4.2 Measuring the level of optimism in the economy

I measure the level of optimism in the economy using CSI, an indicator designed to measure the degree of optimism in the US economy that is updated monthly by the University of Michigan. Specifically, the CSI is constructed using a survey of 500 randomly chosen US households on a monthly basis. The survey asks five questions about current economic conditions, business conditions for the next year, employment conditions for the next five years, and family consumption for the next year.[8] The randomly chosen households are then reinterviewed after six months. The rotating sample is normally compounded with 60% new consumers each month and 40% households interviewed for the second time. The CSI is not published at a state level. Hence, in order to have some cross-sectional variation, I use the regional CSI index, which aggregates consumer expectations at a census regional level.[9]

I also construct an optimism index by calculating the share of CEOs who are considered optimistic according to the options-based criterion of Malmendier and Tate (2008) among the total number of CEOs of firms listed in the NYSE and ranked

[8] Details about the index construction and the text of the questions can be found at this link: http://www.sca.isr.umich.edu/fetchdoc.php?docid=24770

[9] Information about the CSI and the sample used in its construction can be found at the following link: http://www.sca.isr.umich.edu

in Execucomp. This measure of optimism is based on the idea that it is optimal for risk-averse undiversified executives to exercise their own firm's stock option early if the option is sufficiently in the money (Hall and Murphy, 2002). In line with Malmendier and Tate (2008), Campbell et al. (2011), Hirshleifer et al. (2012), and Galasso and Simcoe (2011), I define as optimists those managers who postpone the exercise of options that are at least 67% in the money.

Specifically, for each CEO, I calculate the total realizable value per option by dividing the total realizable value of the exercisable options by the total number of options held by the CEO. The average strike price of the options is calculated as the fiscal year-end stock price minus the average realizable value. The average moneyness of the option is then obtained as the fiscal year stock price divided by the average strike price minus one. If the moneyness of the option is above 67%, I categorize the CEO n in that year t as an optimist. I use only CEOs of enterprises listed on the NYSE. In order to be consistent with the CSI measure, I construct this index at the (census) regional level. The CSI and the ratio of optimistic CEOs to the total number of CEOs of firms listed in NYSE at the regional level after the introduction of IBBEA are reported in Table 3. Figure 1 also reports trend data on the CSI and the ratio of optimistic CEOs.

<<INSERT TABLE 3 HERE>>

<<INSERT FIGURE 1 HERE>>

4.3 Other variables

I complement my bank sample with control variables at the state level, augmenting the econometric models with personal income growth from the Bureau of

Economic Analysis. To account for potential differences among banks in the sample, I also include bank-level control variables. Specifically, I control for bank size (the natural logarithm of bank total assets), the bank income diversification (the share of non-interest income in operating income), the interest on deposit on total interest expenses (interest on deposits on interest expenses), and bank capitalization (total equity on total assets).

In accordance with Dick and Lehnert (2010), as an additional control for market structure, I include the market share of small banks (banks with less than $100 million in assets) in each state and the Herfindahl–Hirschman index. All of the control variables are winsorized at 1%, centered on their mean, and divided by their standard deviation. Table 4 defines the variables used in my analysis, and Table 5 reports the summary statistics for all the variables.

<< INSERT HERE TABLES 4 AND 5>>

The average reported return on assets (ROA) in Table 5 is roughly 1%. The branch restriction index, my policy variable, has a mean of 2.81 and a standard deviation of 1.42. Note that the branch restriction index changes more than once for several states. This feature is particularly important because, as outlined in Bertrand et al. (2004), repeated variations in the policy over time may reduce the autocorrelation issues. The Consumer Sentiment Index (CSI) has a mean of 95.48 in my sample with a standard deviation of 7.35, The measure of optimism, calculated based on the exercising of stock options by CEOs of firms listed on the NYSE, has a mean of 32.70% and a standard deviation of 7.94%.

<< INSERT HERE TABLES 6>>

Table 6 also reports the correlation between the control variables used in the estimation. As expected, the optimism measures are positively correlated each other. However, the correlation between the CSI and the index calculated using the exercising of stock options by CEO of firms listed on the NYSE is only 34%. This low correlation between the optimism measures underscores the distinct natures of the two indexes, which differ in two important ways. First, the University of Michigan randomly selects the sample of consumers underlying the Consumer Sentiment Index, and it also picks up signals from less industrialized regions of the country. The sample underlying the measure of optimism based on the CEO of firms listed in the NYSE is not random and is affected by the geographical clusterization of such firms. Second, the CSI comes from consumer answers to surveys, whereas the index calculated on the exercising of stock options comes from the decisions made by CEOs of firms listed on the NYSE. The ability to analyze the signals of the economy can vary substantially between these two groups. As expected, both optimism variables are positively correlated with personal income growth. Again, this correlation is not very high, measuring 0.34 and 0.41 for the interactions between personal income and, respectively, CSI and the NYSE CEOs index.

4.4 The Exogeneity of interstate branch restrictions

One concern with using regulatory entry barriers as a policy instrument for banking competition is possible endogeneity of the regulation. As outlined by Rice and Strahan (2010), regulatory entry barriers can, in fact, reflect political pressure generated by interest groups. If states with specific characteristics are more likely to deregulate, then the branch index could be correlated with these unobserved state characteristics; thus, its influence on bank performance might reflect not only banking competition but also the effect of unobserved state characteristics. For instance, if states with higher expectations about future economic success are more likely to remove entry barriers, then my branch index could be correlated with credit demand and with the measures of optimism. Rice and Strahan (2010) show that regulatory entry barriers are, in fact, correlated with income growth and with the percentage of banks that have less than $100 million in total assets (small banks). However, they argue that because the differences among states are very persistent over time, this correlation can be ignored by including state fixed effects in the regression models.

Table 7 presents the results from a regression in which I aggregate my data at the state level and then test whether the state characteristics correlate with changes in the branch restriction index after the introduction of state fixed effects and time dummies. In Table 7, I also test whether the level of optimism in the economy is correlated with the regulatory entry barriers after I partial out state and year fixed effects. None of the regression coefficients of personal income, the Herfindahl–Hirschman index, the market share of small banks (banks with total assets below $100 million), the CSI, and the measure of optimism calculated on the option exercising of CEOs has a significant impact on the bank restriction index after controlling for state and year fixed effects.

<<INSERT TABLE 7>>

5 Methodology

To test my research hypotheses, I estimate the following equation:

$$Y_{ijt} = \beta_1 branch\ restriction_{jt-1} + \beta_2 optimism_{kt-1} + \beta_3 branch\ restriction_{jt-1} * optimism_{kt-1} + banks, state\ controls_{ijt-1} + \tau_t + \gamma_j + \varepsilon_{ijt}. \qquad (1)$$

The policy variable ($branch\ restriction_{jt}$) is a count variable ranging from 0 to 4; this feature of the branch restriction index allows me to evaluate the effects of competition at various levels. The optimism variable ($optimism_{kt}$) varies at a regional-year level (for k equal to northeast or north central or south or west). For ease of interpretation of the estimated coefficients, the variable optimism is centered on the minimum and divided by its standard deviation. This adjustment allows me to interpret the coefficient β_1 as the effect of entry barriers on the outcome variable Y_{ijt} when the level of optimism is at its minimum as well as the coefficient β_3 as the effect of a one standard deviation increase in optimism on β_1. Put differently, β_3 indicates how the effect of entry barriers on the outcome variables changes with the level of optimism in the economy. Therefore equation (1) enables me to identify the effect that the level of optimism in the economy has on the relation between banking competition and the outcome variable. In all the estimated regression models, I cluster standard errors at the state level (Bertrand et al., 2004).

6 Results

6.1 The growth of charge-off in banks' lending portfolios

Table 8 reports results for the estimations of equation (1) in which the dependent variable is the growth of loan charge-offs. The first two models are augmented with state fixed effects, the fourth and the fifth models use bank fixed effects. In all of the regression models, I cluster standard errors at the state level. For ease interpretation of the estimated coefficients, the variable CSI is centered on its minimum and divided by its standard deviation.

<<INSERT TABLE 8 HERE>>

The independent variables in Models 1 and 3 are the branch restriction index and its interaction with the level of optimism in the economy. In Models 2 and 4, I use states, banks, and banking market structure controls centered on their means, divided by their standard deviations and winsorized at the 1% level. In all models, I use time fixed effects, and I cluster standard errors at the state level.

Table 8 shows that adding a regulatory barrier to banking competition when the level of optimism in the economy is at its minimum decreases the growth of loan charge-offs. The coefficient on the variable *branch restriction* is negative and statistically significant ($p<0.05$) in all of the regression models. The interaction coefficient of the branch restriction index and the CSI is positive and statistically significant ($p<0.01$) in all models. This evidence confirms my first hypothesis that as the level of optimism increases, the credit losses in banks' lending portfolios in protected banking systems increase.

Specifically, in periods of moderated optimism, approximated by the value of CSI_{kt} in its 25th percentile, an additional entry barrier to banking competition decreases the charge-off growth by 5.53%.[10] Using the sample average of the charge off growth (2.17) as a benchmark, this represents a decrease of 2.55%. However,

[10] This is calculated as -0.10398+0.05595*0.8698, where -0.10398 is the coefficient in the first model on the branch restriction index; 0.05595 is the coefficient of the interaction between the branch restriction index and CSI; and 0.82 is the number of CSI standard deviations (7.358) needed to pass from the minimum (83.6) to the value of CSI at its 25th percentile (90).

when the level of optimism is in the 75th percentile, adding a regulatory restriction to out-of-state entry increases the growth of charge-offs by 5.11%. Using the average growth of charge-offs in my sample, this represents an increase of 2.36%. These estimates are consistent with H1 in showing that the level of optimism increases the link between entry barriers and the charge-off growth in protected banking systems. This result indicates that restricting banking competition through regulatory entry barriers in periods of high optimism leads the credit losses in bank lending portfolios to increase faster. Importantly, the coefficient on the regional CSI is positive but not statistically significant in all of the estimated models. This result indicates that a standard deviation increase in the level of optimism in the economy does not generate an increase in charge-off growth in markets fully open to banking competition, such as those banking systems without any branch restriction.

I show that the above relationship is also confirmed when I introduce bank, state, and banking market structure controls into the analysis. The coefficient on the branch restriction index and its interaction with the level of optimism in the economy are similar in their dimension and in their statistical significance with state or bank fixed effects (Models 3 and 4). Specifically focusing Model 3, which is augmented by bank fixed effects, an additional barrier to out-of-state entry decreases the average charge-off growth in my sample by 3.67% when the level of optimism is in the 25th percentile. Using the sample average of charge-off growth as a benchmark, this represents a decrease of 1.69%. However, when the level of optimism is in the 75th percentile, an additional barrier to out-of-state entry increases the sample average of charge-off growth by 2.44%.

Model 4 in Table 8 also shows that a standard deviation increase in state personal income decreases the growth of charge offs. Interestingly, in Model 4, a standard deviation increase in bank size, approximated by the natural logarithm of banks' total assets, seems to also decrease the growth of charge-offs. This result suggests that larger banks might be more capable of assessing credit risk. Model 4 also shows that higher capitalization is positively associated with higher credit loss growth, suggesting that banks may increase their capitalization to lend to riskier borrowers.

The reported results confirm my first hypothesis by showing that in periods of high optimism, credit losses increase in protected banking systems. The increase in credit losses may be detrimental for banking profits.[11] Therefore any positive effect that branch restriction might have on bank profitability is expected to be less pronounced in periods of high economic optimism. In the next section, I look more closely at bank profitability.

6.2 Bank performance

Table 9 reports results for the estimations of equation (1) in which the dependent variable is the return on assets (ROA), calculated as the net income on total assets. The first two models are augmented with state fixed effects, and the third and fourth models use bank fixed effects.

<<INSERT TABLE 9 HERE>>

[11] Since banks disclose their profits net of credit losses, an increase in loan charge-offs is detrimental to banks' profitability. However, in protected credit environments, banks can also provide loans at higher lending rates in periods of high optimism. Hence, the increase in credit losses might be accompanied by an equal or even greater increase in interest revenues from loans. If this is the case, the final effect on banks' profits will remain unidentifiable. In Section 6.2, I show that this is not the case. Moreover, in unreported results, I adjust the growth of credit losses in different ways to take into account the market power effect. Specifically, I estimate equation (1) using as the dependent variable the ratio of the charge-off growth on the interest revenue growth, and I calculate the difference in the logarithmic growth rate of loan charge-off and interest and fee revenues from loans. Regardless of the adjustment used, the results remain qualitatively and quantitatively very similar to the results estimated using the growth of charge-offs.

Models 1 and 3 show ROA results using as regressors only the branch restriction and its interaction with the level of optimism, but in Models 2 and 4, I use banks, market structure, and bank controls centered on their meana, divided by their standard deviations, and winsorized at the 1% level. In all models, I use time fixed effects. The estimated coefficient shows that an additional barrier to out-of-state entry increases bank profitability when the level of optimism is at its minimum. In all models, the coefficient on the branch restriction index is positive and statistically significant ($p<0.01$). The coefficient on the interaction between the branch restriction index and the level of optimism is negative and significant ($p<0.01$) in all of the models. This evidence is consistent with H2, showing that the level of optimism in the economy substantially decreases the positive effect of regulatory restriction to banking competition on bank performance. Moreover, Models 2 and 4 show that this result does not change if I use bank or state fixed effects and if I augment the regression models with some control variables. This evidence is consistent with the results of the previous section that in protected credit markets, when optimism increases, credit losses also increase. The increase in credit losses is detrimental to bank profitability. The reported results show that any positive effect that regulatory restrictions to banking competition have on ban' profitability is wiped out by an increase in the level of optimism in the economy.

Model 1 shows that in periods of low economic confidence, in the 25th percentile of the variable CSI, an additional barrier to out-of-state entry increases ROA by 0.020%. Using the average ROA in my sample as a benchmark, this represents an approximate increase of 1.828%. If banking competition is extremely limited (four entry barriers), in periods of low optimism, the increase in average bank performance is 7.314%. In periods of high optimism (the value of CSI in the 75th percentile), the effect of an additional barrier to out-of-state entry becomes negative, namely -0.005%, representing -0.468% of the average ROA. This relation shows that a protectionist policy in terms of banking competition (with four entry barriers) in periods of high optimism generates a decrease in average bank performance of 1.872%.

Models 3 and 4 show estimates of the branch restriction index and its interaction with the level of optimism in the economy using bank fixed effects and adding states, banks, and banking market structure controls. I find a negative and significant ($p<0.01$) coefficient on the interaction term between the branch restriction index and the level of optimism in the economy; this effect remains highly significant irrespective of the introduction of control variables.

My findings are consistent with H2: the level of optimism in the economy substantially decreases the link between regulatory restrictions to credit markets and bank profitability. Table 9 also indicates that an increase in personal income at the state level increases bank profitability. Surprisingly, Model 2 shows a negative link between the concentration of the banking system and bank profitability. However, this effect is not strongly statistically significant ($p<0.10$) and becomes statistically indistinguishable than zero when I use bank fixed effects. The reported results also suggest that small banks are less profitable than larger banks. In addition, more capitalized banks seem to report higher performance; however, when bank fixed effects are introduced into the model, this effect loses its statistical significance.

7 Robustness checks

I obtain similar results to those reported in Table 8 and 9 when I replace the CSI with the ratio of CEOs that can be ranked as optimist according to the criterion of Malmendier and Tate (2008). As outlined in session 4.2, the sample underlying the two measures for the level of optimism in the economy is very different. The CSI is calculated on a random sample of consumers, while the NYSE CEOs measure comes from the decisions made by CEOs of firms listed on the NYSE. As shown in Table 6, the correlation between the two measures of optimism is only 34.5%. Moreover, it is also important to stress that the NYSE CEOs measure is affected by some regions having higher industrialization.

<<INSERT TABLE 10 HERE>>

Table 10 reports the results from models similar to those in Tables 8 and 9, where I use the same dependent variables but with the CSI as the measure of optimism. The results on ROA and on the charge off growth are qualitatively very similar to those reported in Tables 8 and 9. Specifically Models 1 and 2 show that adding an entry barrier to banking competition increases banking profits when the level of optimism is at its minimum. This result is not affected if I augment the regression model with control variables. Moreover, the interaction between the branch restriction index and the measure of optimism based on CEO option-exercising is positive and statistically significant ($p<0.1$). This result confirms H2, indicating that the level of optimism in the economy weakens the positive link between the profitability of banks and the branch restriction index. Importantly, the results reported in Table 10 suggest that the profitability of banks operating in banking systems fully open to banking competition is positively associated with the level of optimism in the economy. Using the NYSE CEOs measure of optimism, this relation becomes highly significant ($p<0.01$). This association also remains statistically significant when we look at the growth of charge-offs. The results reported in Table 10 suggest that credit losses in banks' lending portfolios decrease when the level of optimism increases. Model 3 and 4 confirm H1 in showing that in periods of high optimism credit losses increase in protected banking systems.

8 Conclusions

The relation among banking competition, bank profitability, and risk-taking is a central topic in banking research. The literature shows that an increase in competition arising from the liberalization of interstate branching improves banks' ability to screen borrowers and decreases credit losses in banks' lending portfolios (Dick and Lehnert, 2010). Improved lending in more competitive credit markets can attenuate the general tendency of banks to produce overly optimistic estimates of credit risk in periods of improving economic conditions (Allen and Saunders, 2002). Therefore, limiting competition through regulatory entry barriers can have opposing effects on bank profitability. Limiting competition can provide banks with some market power that increases bank profitability. In contrast, it can also decrease the banks' ability to assess credit risk, with a detrimental effect on the performance of banks.

In this paper, I use the regulatory restrictions to banking competition introduced by each state after the 1994 passage of IBBEA to approximate exogenous shocks to banking competition. I argue that the level of optimism in the economy decreases the positive relation between restricted competition and bank profitability. I show that the introduction of regulatory entry barriers to banking competition in periods of high optimism leads the credit losses in banks' lending portfolios to increase. Therefore, even if entry barriers to banking competition provide banks with some monopoly rents that increase bank profitability, the positive effect of market power on bank performance decreases when the level of optimism in the economy increases.

These results have important policy implications. Increasing the competition in banking markets through liberalization policies can be particularly useful when the level of optimism in the economy is very high. This empirical result is consistent with the prediction of the Ruckes' (2004) theoretical model: in periods of improving economic conditions, when the borrower default probability is expected to decrease, the credit quality in the portfolios of banks operating in protected environments tends to deteriorate.

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Figure 1:
Consumer Sentiment Index and the portion of CEOs in the NYSE who do not exercise option more than 67% in the money

This figure reports the evolution of optimism by region in the US after the approval of IBBEA. The blue dotted line is the CSI optimism index based on the University of Michigan survey, and the red line is the index based on the exercise of CEO stock options.

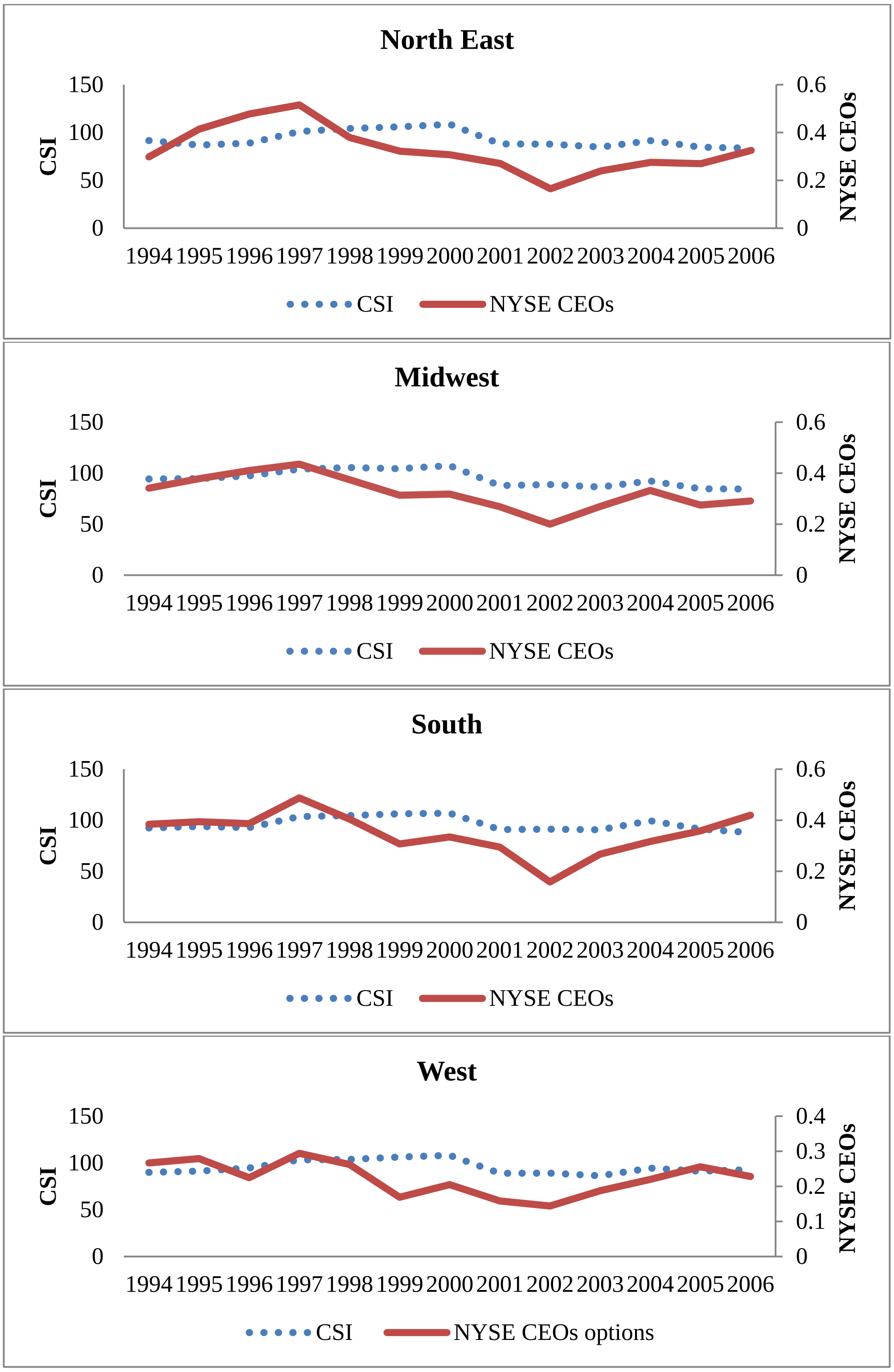

Table 1
Timeline of US credit market liberalization and my sample of banks

The State of Maine permits out-of-state bank ownership	New York joins Maine, beginning the era of interstate branching liberalization	Most of the states lower barriers to interstate branching	**Starting sample year**	IBBEA allows out-of-state entry and permits states to erect entry barriers	The states erect entry barriers to intrastate branching	Last recorded change to entry barriers in Washington	**Last sample year**
1978	1982	1982–1992	1993	1994	1997	2005	2006

Table 2
State and Interstate Branching Laws

This table reports the interstate branching restriction index, the date of the regulation changes, and the specific requirements imposed by each state in regard to a minimum age for branch acquisition, de novo interstate branching, interstate branching by acquisition of a single branch or a portion of an institution, and a statewide deposit cap on branch acquisition. Source (Rice and Strahan 2010)

State	Branch Restriction Index	Effective Date	Minimum Age of a Bank or a Branch for Acquisition	Allows *de novo* Interstate Branching	Interstate Branching by Acquisition of a Single Branch or Portion of an Institution	Statewide Deposit Cap on Branch Acquisitions
Alabama	3	May 31, 1997	5	No	No	30%
Alaska	2	January 1, 1994	3	No	Yes	50%
Arizona	3	September 1, 1996	5	No	No	30%
Arizona	2	August 31, 2001	5	No	Yes	30%
Arkansas	4	June 1, 1997	5	No	No	25%
California	3	September 28, 1995	5	No	No	30%
Colorado	4	June 1, 1997	5	No	No	25%
Connecticut	1	June 27, 1995	5	Yes	Yes	30%
Delaware	3	September 29, 1995	5	No	No	30%
District of Columbia	0	June 13, 1996	No	Yes	Yes	30%
Florida	3	June 1, 1997	3	No	No	30%
Georgia	3	June 1, 1997	5	No	No	30%
Georgia	3	May 10, 2002	3	No	No	30%
Hawaii	3	June 1, 1997	5	No	No	30%
Hawaii	0	January 1, 2001	No	Yes	Yes	30%
Idaho	3	September 29, 1995	5	No	No	None
Illinois	3	June 1, 1997	5	No	No	30%
Illinois	0	August 20, 2004	No	Yes	Yes	30%
Indiana	0	June 1, 1997	No	Yes	Yes	30%
Indiana	1	July 1, 1998	5	Yes	Yes	30%
Iowa	4	April 4, 1996	5	No	No	15%
Kansas	4	September 29, 1995	5	No	No	15%
Kentucky	4	June 1, 1997	5	No	No	15%
Kentucky	3	March 17, 2000	No	No	No	15%

Kentucky	3	March 22, 2004	No	No	No	15%

State	Branch Restriction Index	Effective Date	Minimum Age of a Bank or a Branch for Acquisition	Allows de novo interstate branching	Interstate Branching by Acquisition of a Single Branch or Portion of an Institution	Statewide Deposit Cap on Branch Acquisitions
Louisiana	3	June 1, 1997	5	No	No	30%
Maine	0	January 1, 1997	No	Yes	Yes	30%
Maryland	0	September 29, 1995	No	Yes	Yes	30%
Massachusetts	1	August 2, 1996	3	Yes	Yes	30%
Michigan	0	November 29, 1995	No	Yes	Yes	None
Minnesota	3	June 1, 1997	5	No	No	30%
Mississippi	4	June 1, 1997	5	No	No	25%
Missouri	4	September 29, 1995	5	No	No	13%
Montana	4	September 29, 1995	N/A	N/A	N/A	1%peery
Montana	4	October 1, 2001	5	No	No	22%
Nebraska	4	May 31, 1997	5	No	No	14%
Nevada	3	September 29, 1995	5	Limited	Limited	30%
New Hampshire	4	June 1, 1997	5	No	No	20%
New Hampshire	1	August 1, 2000	5	Yes	Yes	30%
New Hampshire	0	January 1, 2002	No	Yes	Yes	30%
New Jersey	1	April 17, 1996	No	No	Yes	30%
New Mexico	3	June 1, 1996	5	No	No	40%
New York	2	June 1, 1997	5	No	Yes	30%
North Carolina	0	July 1, 1995	No	Yes	Yes	30%
North Dakota	3	May 31, 1997	No	No	No	25%
North Dakota	1	August 1, 2003	No	Yes	Yes	25%
Ohio	0	May 21, 1997	No	Yes	Yes	30%
Oklahoma	4	May 31, 1997	5	No	No	15%
Oklahoma	1	May 17, 2000	No	Yes	Yes	20%
Oregon	3	July 1, 1997	3	No	No	30%
Pennsylvania	0	July 6, 1995	No	Yes	Yes	30%
Rhode Island	0	June 20, 1995	No	Yes	Yes	30%

State	Branch Restriction Index	Effective Date	Minimum Age of a Bank or a Branch for Acquisition	Allows de novo interstate branching	Interstate Branching by Acquisition of a Single Branch or Portion of an Institution	Statewide Deposit Cap on Branch Acquisitions
South Carolina	3	July 1, 1996	5	No	No	30%
South Dakota	3	March 9, 1996	5	No	No	30%
Tennessee	3	June 1, 1997	5	No	No	30%
Tennessee	2	May 1, 1998	5	No	Yes	30%
Tennessee	1	July 1, 2001	5	Yes	Yes	30%
Tennessee	1	March 17, 2003	3	Yes	Yes	30%
Texas	4	August 28, 1995	N/A	N/A	N/A	20%
Texas	2	September 1, 1999	No	Yes	Yes	20%
Utah	2	June 1, 1995	5	No	Yes	30%
Utah	1	April 30, 2001	5	Yes	Yes	30%
Vermont	2	May 30, 1996	5	No	Yes	30%
Vermont	0	January 1, 2001	No	Yes	Yes	30%
Virginia	0	September 29, 1995	No	Yes	Yes	30%
Washington	3	June 6, 1996	5	No	No	30%
Washington	1	May 9, 2005	5	Yes	Yes	30%
West Virginia	1	May 31, 1997	No	Yes	Yes	25%
Wisconsin	3	May 1, 1996	5	No	No	30%
Wyoming	3	May 31, 1997	3	No	No	30%

Table 3
Measure of Optimism in the Economy

This table reports the measure of optimism after the introduction of IBBEA. The Consumer Sentiment Index (CSI) is reported by the University of Michigan. NYSE CEOs option is the ratio of the CEOs who do not exercise stock option that are more than 67% in the money on the total number of CEOs of firms listed on the NYSE and ranked in Execucomp.

	CSI			
	North East	North Central	South	West
1994	91.6	94.3	92.4	90
1995	86.9	94.7	93.9	91.3
1996	88.9	97.4	92.8	94.6
1997	101.1	104	103.6	103.4
1998	104.2	105.5	104.6	103.8
1999	106	104.4	106.3	106.4
2000	108.6	107.4	106.9	108.2
2001	88.1	87.8	90.9	89
2002	87.9	88.9	91.2	89.1
2003	84.8	86.4	90.7	86.3
2004	91.5	92.4	99.5	94.5
2005	84.7	84.7	91.4	91.2
2006	83.6	84.5	87.9	92.9
	NYSE CEOs option			
	North East	North Central	South	West
1994	0.38	0.40	0.46	0.30
1995	0.30	0.34	0.38	0.27
1996	0.41	0.38	0.39	0.28
1997	0.48	0.41	0.39	0.22
1998	0.52	0.44	0.49	0.29
1999	0.38	0.37	0.40	0.26
2000	0.32	0.31	0.31	0.17
2001	0.31	0.32	0.33	0.20
2002	0.27	0.27	0.29	0.16
2003	0.16	0.20	0.16	0.14
2004	0.24	0.27	0.27	0.19
2005	0.28	0.33	0.32	0.22
2006	0.27	0.28	0.36	0.26

Table 4
Variable Descriptions

Variable	Description	Database
Return on Asset (ROA)	The ratio of net income on total asset the (riad4340/ rcfd2170)	Call Reports
Charge off on growth	The growth of loan charge off is constructed as the loan charge off (riad4635) at time t divided by the loan charge off at time t-1	Call Reports
Branch restriction index	The changes in the branch restriction index	Rice and Strahan (2010)
CSI	The consumer sentiment index (CSI) measures the level of optimism in the US economy using the answers of US households selected randomly on a monthly basis	Thomson Reuters/ University of Michigan
NYSE CEOs option	The share of executives leading firms listed in the NYSE who did not exercise stock option that are more than 67% in the money	Execucomp
State personal income growth	The growth of personal income at the state level	NBER database
Herfindahl–Hirschman index	The market concentration index at the state level, calculated as the sum of the banks squared market shares in terms of total asset at the state level	Call Reports
Small bank share	The state share of small banks (less than 100M $ of total asset)	Call Reports
Log (total assets)	The natural logarithm of total assets (rcfd2170)	Call Reports
The share of non-interest income in operating income	A measure of income diversification (variables riad4079/ riad4000)	Call Reports
Interest on deposits on interest expenses	This variable is the share of interest paid on deposits on total interest expenses (riad4170/ riad4073)	Call Reports
Equity on Total Assets	This variable is the banks' capitalization calculated as Total Equity on Total Asset (rcfd3210 /rcfd2170)	Call Reports

Table 5
Summary Statistics

Variable	Observations	Mean	Standard Deviation	Min	Max
ROA	105,073	0.0108	0.0067	-0.0405	0.0331
Charge off growth	105,073	2.1702	4.2737	0.0000	31.6000
Branch restriction index	105,073	2.8080	1.4176	0.0000	4.0000
Consumer Sentiment Index	105,073	95.4783	7.3580	83.6000	108.6000
NYSE CEOs index	105,073	0.3270	0.0794	0.1440	0.5156
State personal income growth	105,073	1.0460	0.0188	0.9536	1.0931
Herfindahl–Hirschman index	105,073	0.1108	0.1007	0.0074	0.9096
Small bank share	105,073	0.0054	0.0299	0.0000	0.9590
Log (total assets)	105,073	11.5571	1.2656	8.9229	15.9424
Non-interest income on operating income	105,073	0.1079	0.0764	0.0067	0.6002
Interest on deposits on interest expenses	105,068	0.9100	0.1461	0.1915	1.0000
Equity on total assets	105,073	0.1018	0.0352	0.0563	0.4495

Table 6
Correlation Table

	Branch restriction index	Consumer Sentiment Index	NYSE CEOs index	State personal income growth	Herfindahl–Hirschman index	Small bank share	Log (total assets)	Non-interest income on operating income	Interest on deposits on interest expenses	Equity on total assets
Branch restriction index										
Consumer Sentiment Index	0.034									
NYSE CEOs index	0.133	0.345								
State personal income growth	0.041	0.346	0.410							
Herfindahl–Hirschman index	-0.307	-0.070	-0.190	-0.089						
Small bank share	-0.064	-0.011	-0.050	-0.012	0.110					
Log (total assets)	-0.252	-0.083	-0.106	-0.040	0.183	0.424				
Non-interest income on operating income	-0.038	-0.092	-0.127	-0.067	0.078	0.207	0.273			
Interest on deposits on interest expenses	0.096	0.107	0.043	0.011	-0.074	-0.176	-0.406	-0.196		
Equity on total assets	-0.023	-0.016	-0.016	-0.004	0.040	-0.042	-0.153	0.022	0.043	

Table 7
The exogeneity of the branch restriction index

This table reports the coefficient on a regression model where I use the branch restriction index as a dependent variable to test any residual correlation between the policy variable, my measure of optimism, and some state characteristics after partialling-out state and year fixed effects. Specifically, the Herfindahl–Hirschman index (HHI) and the share of banks with less than $100 million in total assets (small bank share) are calculated by aggregating my data at the state level. Personal income is also at the state level and comes from the NBER database. The CSI and the NYSE CEO are at the regional level.

VARIABLES	(1) $branch\ restriction_{jt}$	(2) $branch\ restriction_{jt}$	(3) $branch\ restriction_{jt}$	(4) $branch\ restriction_{jt}$	(5) $branch\ restriction_{jt}$
$Personal\ Income_{jt-1}$	-1.4505				
	(2.6500)				
HHI_{jt-1}		-1.0574			
		(0.7325)			
$Small\ bank\ share_j$			-1.5828		
			(1.8647)		
CSI_{kt-1}				0.0103	
				(0.0233)	
$NYSE\ CEO_{kt-1}$					-1.0430
					(1.5659)
$Constant$	5.0662*	3.8712***	3.6763***	2.7095	3.8801***
	(2.7545)	(0.2724)	(0.2102)	(1.9006)	(0.5324)
$State\ FE$	Y	Y	Y	Y	Y
$Year\ FE$	Y	Y	Y	Y	Y
$Observation$	663	663	663	663	663

Standard errors in parentheses are clustered at the state level
*** p<0.01, ** p<0.05, * p<0.1

Table 8
The Growth of Loans Charge Off

This table presents the results for the estimation of the following equation:

$$\frac{loan\ charge\ off_{ijt}}{loan\ charge\ off_{ijt-1}} = \beta_1 branch\ restriction_{jt-1} + \beta_2\ CSI_{kt-1} + \beta_3 branch\ restriction_{jt-1} * CSI_{kt-1} + banks, state\ controls_{ijt-1} + \tau_t + \gamma_j + \varepsilon_{ijt}$$

The growth of charge-offs is calculated as the value of the variable at time t divided by the value of the same variable at time t-1. In the first two models, I include state fixed effects, but in the third and fourth models I use bank fixed effects. Time dummies are also added into all models. Standard errors are clustered at the state level. The state, banking market structure, and bank controls are centered on their means, divided by their standard deviations, and winsorized at the 1% level. For an easier interpretation of the parameters of interest, the variable CSI is centered on its minimum and divided by its standard deviation.

	Dependent Variable: $\frac{loan\ charge\ off_{ijt}}{loan\ charge\ off_{ijt-1}}$			
	(1)	(2)	(3)	(4)
$branch\ restriction_{jt-1}$	-0.10398***	-0.10023***	-0.07762**	-0.08611***
	(0.03441)	(0.03143)	(0.03222)	(0.03211)
CSI_{kt-1}	0.01108	0.08731	-0.07369	0.02956
	(0.08635)	(0.08066)	(0.07650)	(0.07787)
$branch\ restriction_{jt-1} * CSI_{kt-1}$	0.05595***	0.05384***	0.04710***	0.04931***
	(0.01440)	(0.01355)	(0.01346)	(0.01336)
$Personal\ Income_{jt-1}$		-0.09332***		-0.08864***
		(0.02123)		(0.02169)
HHI_{jt-1}		0.03491		0.00803
		(0.05236)		(0.05485)
$Small\ bank\ share_{jt-1}$		-0.00917		-0.11113***
		(0.01236)		(0.03592)
$\log(TA_{ijt-1})$		-0.21115***		-0.52679***
		(0.02380)		(0.13173)
$\frac{Non\ Interest\ Income_{ijt-1}}{Operating\ Income_{ijt-1}}$		-0.14343***		-0.18528***
		(0.01848)		(0.04136)
$\frac{Interest\ on\ deposits}{Interest\ Expenses_{ijt-1}}$		-0.04886**		-0.05850***
		(0.01886)		(0.01795)
$\frac{Equity_{ijt-1}}{Total\ Asset_{ijt-1}}$		0.05953**		0.17446***
		(0.02673)		(0.05850)
$Constant$	2.01776***	1.92467***	2.06722***	1.88520***
	(0.14132)	(0.12789)	(0.12987)	(0.13415)
$Observations$	105,073	105,073	105,073	105,073
$Year\ fixed\ effects$	Y	Y	Y	Y
$State\ fixed\ effects$	Y	Y	N	N
$Bank\ fixed\ effects$	N	N	Y	Y

Standard errors in parentheses are clustered at the state level
*** p<0.01, ** p<0.05, * p<0.1

Table 9
Regression on Bank Performance

This table presents the results for the estimation of the following equation:

$$ROA_{ijt} = \beta_1 branch\ restriction_{jt-1} + \beta_2 CSI_{kt-1} + \beta_3 branch\ restriction_{jt-1} * CSI_{kt-1} + banks, state\ controls_{ijt-1} + \tau_t + \gamma_j + \varepsilon_{ijt}$$

The dependent variable is the return on assets (ROA). In the first two models, I include state fixed effects, but in the third and fourth models I use bank fixed effects. Time dummies are also added into all models. Standard errors are clustered at the state level. The state, banking market structure, and bank controls are centered on their means, divided by their standard deviations, and winsorized at the 1% level. For an easier interpretation of the parameters of interest, the variable CSI is centered on its minimum and divided by its standard deviation.

	Dependent Variable: ROA_{ijt}			
	(1)	(2)	(3)	(4)
$branch\ restriction_{jt-1}$	0.00031***	0.00026***	0.00026***	0.00025***
	(0.00010)	(0.00009)	(0.00009)	(0.00008)
CSI_{kt-1}	0.00058*	0.00021	0.00060*	0.00033
	(0.00034)	(0.00027)	(0.00030)	(0.00025)
$branch\ restriction_{jt-1} * CSI_{kt-1}$	-0.00013***	-0.00010***	-0.00010***	-0.00010***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
$Personal\ Income_{jt-1}$		0.00033***		0.00024***
		(0.00010)		(0.00009)
HHI_{jt-1}		-0.00027*		-0.00021
		(0.00016)		(0.00014)
$Small\ bank\ share_{jt-1}$		-0.00027***		-0.00003
		(0.00007)		(0.00006)
$\log(TA_{ijt-1})$		0.00176***		0.00129***
		(0.00011)		(0.00023)
$\frac{Non\ Interest\ Income_{ijt-1}}{Operating\ Income_{ijt-1}}$		0.00032**		0.00030**
		(0.00013)		(0.00012)
$\frac{Interest\ on\ deposits}{Interest\ Expenses_{ijt-1}}$		0.00015**		0.00010***
		(0.00006)		(0.00003)
$\frac{Equity_{ijt-1}}{Total\ Asset_{ijt-1}}$		0.00163***		0.00008
		(0.00012)		(0.00018)
$Constant$	0.00936***	0.01051***	0.00952***	0.01012***
	(0.00061)	(0.00046)	(0.00052)	(0.00041)
$Observations$	105,073	105,073	105,073	105,073
$Year\ fixed\ effects$	Y	Y	Y	Y
$State\ fixed\ effects$	Y	Y	N	N
$Bank\ fixed\ effects$	N	N	Y	Y

Standard errors in parentheses are clustered at the state level
*** p<0.01, ** p<0.05, * p<0.1

Table 10
Robustness

This table presents the results for the estimation of the following equation:

$$Y_{ijt} = \beta_1 branch\ restriction_{jt-1} + \beta_2 NYSE\ CEO_{kt-1} + \beta_3 branch\ restriction_{jt-1} * NYSE\ CEO_{kt-1} + banks, state\ controls_{ijt-1} + \tau_t + \gamma_j + \varepsilon_{ijt}$$

The dependent variable Y_{ijt} is the return on assets (ROA) in the first two models and the growth of charge-offs in Models 3 and 4. In all models, I include state fixed effects and time dummies. Standard errors are clustered at the state level. The state, banking market structure, and bank controls are standardized and winsorized at the 1% level. For an easier interpretation of the parameters of interest, the variable $NYSE\ CEO_{kt}$ is centered on its minimum and divided by its standard deviation.

	Dependent Variable: ROA_{ijt}		Dependent Variable: $\frac{loan\ charge\ off_{ijt}}{loan\ charge\ off_{ijt-1}}$	
	(1)	(2)	(3)	(4)
$branch\ restriction_{jt-1}$	0.00019*	0.00018*	-0.08560**	-0.09573**
	(0.00011)	(0.00010)	(0.03733)	(0.03617)
$NYSE\ CEO_{kt-1}$	0.00085***	0.00075***	-0.16534**	-0.15550**
	(0.00012)	(0.00012)	(0.07456)	(0.07342)
$branch\ restriction_{jt-1} * NYSE\ CEO_{kt-1}$	-0.00006*	-0.00007**	0.04298***	0.04701***
	(0.00004)	(0.00003)	(0.01408)	(0.01381)
$Personal\ Income_{jt-1}$		0.00029**		-0.07505***
		(0.00012)		(0.02263)
HHI_{jt-1}		-0.00027*		0.03641
		(0.00016)		(0.05115)
$Small\ bank\ share_{jt-1}$		-0.00027***		-0.00893
		(0.00007)		(0.01233)
$\log(TA_{ijt-1})$		0.00176***		-0.21059***
		(0.00011)		(0.02389)
$\frac{Interest\ Income_{ijt-1}}{Operating\ Income_{ijt-1}}$		0.00033**		-0.14411***
		(0.00013)		(0.01824)
$\frac{Interest\ on\ deposits}{Interest\ Expenses_{ijt-1}}$		0.00015**		-0.04823**
		(0.00006)		(0.01890)
$\frac{Equity_{ijt-1}}{Total\ Asset_{ijt-1}}$		0.00163***		0.06029**
		(0.00012)		(0.02666)
$Constant$	0.00781***	0.00841***	2.58609***	2.53991***
	(0.00058)	(0.00051)	(0.27164)	(0.26585)
$Observations$	105,073	105,073	105,073	105,073
$Year\ fixed\ effects$	Y	Y	Y	Y
$State\ fixed\ effects$	Y	Y	Y	Y

Standard errors in parentheses are clustered at the state level
*** p<0.01, ** p<0.05, * p<0.1

Chapter 3: Corporate culture and innovation

Abstract: Innovation is the main driver of economic growth. However, the determinants of firms' ability to innovate are still widely discussed among academics and policymakers. In this paper, we posit that corporate culture plays a crucial role in the firms' ability to innovate. Following the Competing Value Framework, we identify four different corporate cultures: competition-oriented, control-oriented, creativity-oriented, and collaboration-oriented. We assume that the words and the language used by members of listed firms in their official documents reveal some information on the culture they develop over time. We then measure corporate culture, analysing the 10-K of listed firms. We show that firms with a creativity-oriented corporate culture invest more in R&D and obtain better results from their investment in innovation. This evidence suggests creativity-oriented firms are better innovators. Consistently with this finding, we also show that this corporate culture is associated with higher firm value.

1. Introduction

Innovation can be defined as the introduction of new goods, new methods of production, the establishment of new markets, or new forms of supply. Innovation plays a key role in boosting economic growth (Aghion et al., 2013) and understanding the determinants of firms' ability to innovate, has been the focus of academics and policymakers[12] in the last few decades. Corporate culture can potentially catalyse firms' innovation processes since it can boost employees' motivation (Edmans, Li, and Zhang, 2014) and improve firms' working environments (Price, 2007). The belief that corporate culture relates to the firms' innovation ability is also widely held among listed firms: 85% of S&P 500 companies have a section dedicated to corporate

[12] See OECD (2007)

culture on their website, in which 80% of them advertise innovation as a corporate value (Guiso et al., 2014). Some examples are Intel, that in its web page dedicated to corporate culture states that “passion for innovation helps us maintain our role as a technology leader”, or 3M that defines W. McKnight, the company chairman from 1949 to 1966 as “a business philosopher, since he created a corporate culture that encourages employee initiative and innovation”. There is a growing academic literature on corporate culture addressing important issues, such as the link between firm performance and the employees’ perception of corporate values (Guiso et al., 2013), or the role played by corporate culture in moderating the probability of CEO turnover (Fiordelisi and Ricci, 2014). Surprisingly, no empirical papers that analyse the relationship between innovation and corporate culture exist. This paper aims to fill this gap by answering the following research questions: Does corporate culture influence firms’ investment in innovation? Is the higher investment in innovation reflected in firms’ valuation?

We show that corporate culture plays an important role in firms’ propensity to undertake innovative projects. Specifically, we document three main results. First, we find that firms more oriented towards creativity (i.e. creativity-oriented), invest more in innovation. Second, we document that firms with a corporate culture geared towards implementing greater innovation investment generate higher innovative output even after controlling for R&D expenses. Third, we outline that the same corporate culture that increases investment in innovation and firms’ patenting activity is, also, positively associated to firm value.

We measure corporate culture by assessing corporate financial statements and assume that words and language used by members of listed firms in their official documents (named “vocabulary”) reveal some information on the culture they adhere to (Levinson, 2003). By using the competing values' framework (CVF) (Cameron et al., 2006, and Quinn and Rohrbaugh, 1983) to define four cultural dimensions (create, collaborate, compete, and control), we identify a set of words for each cultural dimension, and subsequently frame them by using the Harvard Psychological dictionary. We then run a text analysis (Stone et al., 1966) on the 128,489 10-K reports, which are available in the SEC's Edgar database to estimate a firm-year specific score for each corporate cultural dimension of the CVF.

We approximate investment in innovation by R&D expenditure, and firms' innovative output by their patenting activity, which is the number of patents applied for in each year of our sample from the U.S. Patents and Trademarks Office (Hirshleifer et al., 2012). We collect our firms' number of patents and patent citations from the NBER patent database, which comprises 3.2 million patent grants and 23.6 million patent citations. The latest release of the NBER patent database starts in 1976 and ends in 2006. Since it takes approximately two years for a patent to be granted, and patents are included in the database only if they are eventually granted, patents applied for in 2005 and 2006 may not yet exist in the database; for this reason, following the approach of Hirshleifer et al. (2012), we end our analysis in 2004.

As outlined in Griliches, Pakes, and Hall (1987), the patent count approximates innovation success in an imperfect manner because patents differ substantially in their importance. Hence, the patent citations better capture the technological and economic significance of patents (Trajtenberg, 1990; Hall, Jaffe, and Trajtenberg, 2005). However, our patent citations variable suffers from problems of truncation, since for patents granted in years closer to the final year of the NBER database, less time is available to obtain citations. To address this issue, we follow Hall, Jaffe, and Trajtenberg, (2005) who adjust the patent citations multiplying the citations count by the weighting[13] index, also available in the NBER database. Hence, our database is the intersection between the Edgar database, Compustat, Execucomp, CRSP data and the NBER patent, and consists of 1,205 listed firms from 1995 to 2004, with 4,976 firm-year observations.

This paper expands the existing literature since it is the first paper analysing the relationship between corporate culture and firms' innovation process. We show that a creative corporate culture is positively associated with R&D investment and innovative output. We also show a positive relation between a creativity-oriented corporate culture and firm value. These results are in line with the findings of Guiso et al. (2013), who show that innovation is the most advertised value on listed company webpages dedicated to corporate culture. We show that listed firms tend to advertise their innovative corporate culture, since it is, on average, positively related to firm value.

The paper proceeds as follows: we describe our measures for corporate culture in section two; section three describes our sample; in section four, we examine the relation between corporate culture and innovative activities; section five analyses the association between corporate culture and firm value; in section six, we present an instrumental variable approach to alleviate endogeneity concerns about our cultural variables; finally, we formulate our conclusions in Section seven.

2. Theoretical framework

Corporate culture is a general concept that comprises "a set of norms and values that are widely shared and strongly held throughout the organization" (O'Reilly and

[13] Specifically we multiply the citations count (the variable allcites in the NBER database) with the weighting index (the variable hjtwt in the NBER database) to account for the truncation. The weighting index is constructed to account for patent obsolescence and for the 2006 truncation.

Chatman, 1996). Consistent with Deal and Kennedy (1982), Peters and Waterman, (1982), Wilkins and Ouchi (1983) and Schein (1992), the definition of O'Reilly and Chatman (1996) outlines that corporate culture can influence economic outcomes, such as an organization’s effectiveness and value creation. As we focus in this paper on the role of corporate culture in affecting firms’ innovation ability, we need to define culture dimensions in a precise way. To this purpose, we follow Cameron et al. (2006), and we use the competing value framework (CVF) that defines four culture dimensions: control, competition, collaboration, and creation.

The CVF framework draws on Quinn and Rohrbaugh (1983)'s, which is a framework widely used in the literature (Hartnell et al., 2011; Ostroff et al., 2003; Schneider et al., 2013). The CVF defines corporate culture as internally or externally oriented. An internally oriented firm can have a collaboration-oriented culture (termed “clan culture type” in the CVF), which has an employee focus aiming at developing competencies and strengthening organizational culture. The intuition is that this affiliation engenders positive employee attitudes. This culture aims to develop cooperation and the participation of employees in corporate decisions, i.e. it clarifies and reinforces organizational values, norms, and expectations, developing employees and cross-functional work groups, implementing programmes to enhance employee retention. Companies promoting this culture can be successful, since they succeed in retaining their human resource. An internally oriented culture can also be control-oriented (also called “hierarchy culture”). This corporate culture is structured on clear and rigid mechanisms. The goal of a control-oriented firm is to create value improving efficiency, enhancing the effectiveness of internal processes (e.g., improving systems, and technology). Companies with this culture usually have standardized procedures and are focused on rule reinforcement and uniformity.

The CVF also outlines two externally oriented corporate cultures. The first is the competition-oriented culture (named “market culture type”). Firms with this culture focus on external effectiveness, by aiming to enhance competitiveness and accentuating the importance of fast response and customer focus. Customer and shareholder judgment is fundamental for competition-oriented firms. The other culture type is the creativity-oriented culture (termed “adhocracy” in the CVF), which focuses on innovation in products and services. The firm encourages employees to share ideas, to have vision, and constantly change, e.g., allowing for freedom of thought and action among employees, such that rule breaking and reaching beyond barriers are common characteristics of the organisation's culture. These companies usually encourage radical new process breakthroughs and innovations, and develop new technologies that redefine entire industries.

<< INSERT FIGURE 1 >>

In this paper, we test the intuitive belief that a creativity-oriented corporate culture does indeed improve firms’ ability to innovate. Specifically, we posit that creativity-oriented corporations are able to obtain valuable output from their investment in research and development.

H1: A creativity-oriented corporate culture is positively associated with the investment in R&D firms patenting activity and with firm value.

Hypothesis H1 implicitly suggests that firms with a creativity-oriented corporate culture are able to translate their investment in R&D into firm value.

The effects of the other three corporate cultures that are part of the competing value framework with respect to firms’ innovation activity are more ambiguous.

Innovation projects are risky and are associated with uncertain outcomes (Manso, 2011). Therefore, firms with a corporate culture more orientated to competition may incur lower R&D expenses, as they may not increase performance in the short-run. However, firms with a competition-oriented corporate culture may still invest in R&D in order to differentiate their products and “escape competition” (Aghion et al., 2005). Similarly, a collaboration-oriented corporate culture can be particularly successful in retaining competences and human capital, an aspect that can have a positive effect on a firm’s innovation activity. On the other hand, the commitment to the internal functioning and a high level of satisfaction can lead collaboration-oriented firms to refrain from initiating innovative projects, and to remain loyal to the current products and the internal structures. In a similar fashion, control-oriented corporate cultures committed to the smooth functioning of internal process, can increase the innovation activity in order to improve cost efficiency. Also, firms with a control-oriented corporate culture may dislike the uncertainty embedded in innovative projects, which restrains their investments in innovation. Therefore, we refrain from formulating explicit hypotheses with regard to the link between innovation ability and corporate cultures with a competition-, control-, and collaboration-orientation.

3. Data and Descriptive statistics

We construct our sample by combining data obtained from five different databases: (1) accounting variables from Compustat, (2) market information from CRSP, (3) 10-Ks used to calculate the corporate culture proxies from the SEC Edgar Database, (4) executives’ characteristics from Execucomp, and (5) patent information from the NBER database. Hence, the sample combines Compustat, CRSP, Edgar Execucomp, and the NBER patent databases. Financial firms (i.e. firms with four digit SIC code from 6000 to 6999) are excluded from the analysis. The resulting sample consists of 1,205 firms over a time window spanning from 1995 to 2004, and engendering a total of 4,976 firm-year observations. A description of all the variables is reported in Table 1, and the summary statistics are reported in Table 2.

<< INSERT TABLE 1 AND 2>>

Table 2 reports that the average investment in R&D represents 4.32% of firms’ assets, while the average Tobin’s Q is 2.28 with a standard deviation of 1.62. Table 2 also reports how a competition-oriented culture is the most frequently adopted by listed firms: on average, words capturing a competition orientation represent 3.58% of the words used in firms’ 10Ks, whereas words reflecting a control-oriented corporate culture represent on average 2.04%. Words related, respectively, to collaboration and creation-oriented cultures represent on average 1.01%, and 0.70% of the total number of words in the 10Ks.

3.1 Measuring Corporate Culture

To quantitatively measure the four dimensions of corporate culture in the spirit of Cameron et al. (2006), we use text analysis. Text analysis is a method used to systematically analyse the characteristics and the content of a specific text (Stone et al., 1966). To measure corporate culture, we assume that the words and the language used by the members of a listed firm (named “vocabulary”) reveal some information on the culture they develop over time (Levinson, 2003).

We argue that the features of any firm are reflected in its official written documents and that our text analysis is able to structurally examine the content of firms' official documents (namely, 10-K reports). The extant finance and management literature makes widely use of text analysis (e.g., Antweiler and Murray, 2004; Hoberg and Hanley, 2010; Hoberg and Phillips, 2010; Li, 2008; Loughran and McDonald, 2011; Tetlock, 2007; Tetlock et al., 2008). To estimate our culture dimensions, which we define in Figure 1 (collaboration, competition, control, and creation) we identify a large set of words for each cultural dimension. Each set of words is selected by means of a two-steps process. First, we select the synonyms suggested by Cameron et al. (2006) to identify each cultural dimension. Second, all words selected during the first step are identified in the Harvard-IV Dictionary for additional synonyms. Loughran and McDonald (2011) point out that the use of the Harvard dictionary in text analysis significantly decreases the impact of a researcher's subjectivity in terms of word selection. As an example, words like "cooperation" are associated with the word "collaborate" in the Harvard Dictionary, and a relatively high frequency of their use in corporate documents suggests that the company has a collaboration-oriented culture. Words such as "performance" or "achieve" are associated with a competition-oriented corporate culture. Words such as "dream, begin, elaborate" are more associated with "create", and a relatively high frequency of their use in corporate documents suggests that the company has a creativity-oriented culture. Words such as "boss, efficiency, caution" are considered synonyms for "control" and point toward a control-oriented culture. We calculate the prominence and the frequency with which our synonyms are reported in each annual 10-K and we use the resulting percentage to approximate cultural orientation. For instance, the "competition-oriented" variable equals to 5 if the synonyms approximating this culture dimension represent 5% of all words in the entire document. The correlation between our variables is reported in Table 3.

<< INSERT TABLE 3>>

3.2 Other Variables

We argue that firms' innovation ability is affected by their corporate cultures. To test this broad hypothesis, following Aghion et al. (2013), we also control for: firm size (the natural logarithm of total sales), capital intensity (the net property, plant and equipment related to the number of employees), and firm age (the current fiscal year minus the first year when the firm appears in Compustat). Moreover, since higher innovative output is likely to be associated with larger stock returns, we also control for the buy-and-hold return over the fiscal year. Galasso et al. (2011) and Hirshleifer et al. (2012) show that innovation activity increases with managerial overconfidence, which is why we include a proxy for CEO overconfidence based on the option-based criterion of Malmendier and Tate (2005, 2008). Here, the idea is that it is optimal for risk-averse, undiversified executives to exercise their own firm's stock options early if the option is sufficiently in the money (Hall and Murphy 2002). Our control variable Longholder takes the value 1 if the CEO postpones the exercise of options that are at least 67% in the money (the standard criterion also used by Malmendier and Tate 2005, 2008; Cambell et al., 2011; Galasso et al., 2011; Hirshleifer et al., 2012).[14] Aghion et al. (2013) outline that institutional ownership is an important determinant of firm innovation activity; for this reason, we also include institutional ownership as a control variable.

[14] More specifically, for each CEO, we divide his total realizable value of the exercisable options by the total number of options he holds. The average strike price of the option is deduced by subtracting the average realizable value from the stock price at the end of the fiscal year. The average moneyness of the option is then obtained by dividing the stock price at the end of the fiscal year by the average strike price, and subtracting one. If the moneyness of the stock option is above 67%, we rank the executive k in that year t as a longholder.

4. Corporate culture, the investment in innovation, and the patenting activity of firms

Our broad hypothesis is that a creative corporate culture is positively associated with a firm's propensity to undertake innovative projects. Specifically, we expect that a creation-oriented corporate culture is positively associated with a firm's innovation activities. In the first step of our analysis, we test if R&D investment and firms' patenting activity are positively associated with a creative corporate culture.

Model (1) of Table 4 reports the results of a relation between R&D investment and corporate culture alone. We progressively include in Models (4) to (8) firm dimension, capital intensity, market-based firm performance, firm age, a measure of CEO's confidence (Longholder) and the share of the firm controlled by institutional investors. For an easier interpretation of the coefficients, we standardize all the independent variables centring them on their mean and dividing each variable by its standard deviation. We find consistent results that a corporate culture fostering creativity is positively associated with the firms' innovation activity. In this type of culture, employees are stimulated to be creative and take risks. They are expected to thrive in a change-oriented environment. We also control for a firm's scores on other dimensions of corporate culture. For instance, we find that R&D intensity goes hand in hand with a control-oriented environment (Control), which focuses on efficiency and rule-driven processes. R&D intensity is weaker in firms concentrating on market share and productivity (Compete). More specifically, Model (1) shows that one standard deviation in our variable create is related to an increase of 0.18 ($p<0.1$) in R&D investment; this increase represents 4.35% of the average R&D intensity in our sample. This result is unaffected if we add control variables to the regression model.

Specifically, Model (4) shows that a standard deviation increase in our variable create is associated with an increase in the investment in research and development of 0.21 (p<0.05); this represents 4.96% of the average investment in R&D in our sample.

Model (2) and Model (3) also report the association between our variable create and firms' patenting activity. In Model (2) and in model (3), the dependent variable is respectively the natural logarithm of one plus the patent count, and one plus the citations received by the patents weighted using the variable "hjtwt" in the NBER dataset in order to account for truncation (the fact that recently granted patents have had a more limited time to get citations). Model (2) and (3) confirm our earlier findings: a corporate culture stimulating creativity leads to higher innovative output as captured by patent count and patent citations. When the Creativity score augments by one standard deviation, the patent count goes up by 3.95% (p<0.05) while patent citations by 7.13% (p<0.10). Models (5) and (6) also confirm that patent count and patent quality continue to be correlated with a creative corporate culture if we augment our regression model with additional control variables at firm level. Furthermore, in Models (5) and (6) we also add R&D expenses on total assets to the analysis. As outlined in Aghion et al. (2013) and Hirshleifer et al. (2012), to test for a higher ability to innovate, we need to control for the R&D stock when analysing R&D productivity, i.e. the ability of firms to obtain higher innovative output from R&D investment. Therefore, Models (5) and (6) report the association between our variable create and the firm's patenting activity controlling for investment in R&D. Our results indicate that firms with a creativity-oriented corporate culture also have higher innovation productivity, meaning that they produce higher innovative output following investment in R&D. A standard deviation increase in our variable create is associated with a 4.60% increase in the patent count and to a 7.90% increase in the quality of the patents represented by the patent citations. The reported results also confirm H1 outlining how a creativity-oriented corporate culture is associated with an increase in patent quality, even after controlling for investment in R&D. The last two models in Table 4 also report results using industry fixed effects instead of firm fixed effects (Models (7) and (8)), and focus on the differences between firms within the same industry. The reported results show that the estimated coefficients are larger than those estimated using firm fixed effects outlining some persistency in our cultural variables. In conclusion, our results indicate that a creative-oriented corporate culture is associated with higher innovation output. Therefore, it is possible that firms with a higher score in our variable create are more able to translate R&D investment in firm value.

<< INSERT TABLE 4>>

5. Corporate culture, the investment in innovation and firm value

In this section, we turn our focus to firm value as expressed by Tobin's Q. We posit that firms with a creation-oriented corporate culture are more able to create value from their investment in R&D. To test this broad hypothesis, we regress Tobin's Q on R&D investment and our culture variables plus some controls. In the regressions reported in Table 5 variables are standardized and winsorized at 1% level and all the regressions are run using time dummies and, as indicated, industry or firm fixed effects. Standard errors reported in parenthesis are clustered at industry level.

In Model (1), we regress firm value on the variable create alone, and we show that a one standard deviation increase in our variable create is related with an increase in firm value of 10.03% ($p<0.05$), that represents the 4.39% of the average Tobin's Q in our sample. This evidence suggests that corporate culture relates to firm value through innovation. A possible explanation of this result, which is consistent with H1, is that corporate culture increases firms' ability to innovate. Therefore, in Models (2), (3) and (4) we also add R&D expenses on total assets to the analysis. As expected, the R&D investment is positively associated with firm value. However, most importantly, Models (2) and (3) show that our previous result on creation-oriented corporate culture is not affected if we add the R&D expenses to the regression on firm value. Specifically, Model (2) shows that the positive association between our variable create and firm value is still statistically significant ($p<0.10$) if we add R&D expenses as additional control variables to the analysis and if we use firm fixed effects. Model (3) shows how a one standard deviation increase in our variable create, is associated with an increase in firm value of 6.23% ($p<0.10$), which represents 2.73% of the average firm value in our sample even after controlling for some firm, executives and shareholders characteristics. Thus, these results confirm H1 according to which a creative corporate culture is positively associated with firm value. This positive association may flow through investment in innovation. However, the decision to invest in innovation can also be affected by unobservable firms characteristics. These unknown characteristics may in turn correlate with both firm value and firms' patenting activity, thus, generating a bias in the coefficients reported so far. Moreover, it also possible that creation-oriented corporate culture increases just before the innovation output only because firms advertise their innovation activity in their 10-K, potentially generating a reverse causality issue. In the next session, we rely on exogenous shocks to firms' investment in R&D to alleviate both these concerns.

<< INSERT TABLE 5 >>

6. Instrumenting create with the changes in R&D tax-credit

In this section, we use State-level R&D tax credit as instrument for our variable create. State-level R&D tax credits vary substantially over time and state. The variation over States can be significant; there are States that have never introduced any tax credit on R&D as Kentucky, South Dakota or Tennessee and States such as Arizona that introduced a tax credit of 20% for R&D expenditure in 1993. State level tax incentives for R&D can also vary substantially across time within the same State; for instance, California introduced a tax credit of 8% in 1987 that increased to 11% in 1997 and 15% in 2000. The data on tax credit comes from Wilson (2009)[15] that shows how state level tax incentives for R&D increase firms' investment in R&D. Bloom et al.(2013) also use these tax credits as instruments for firm investment in R&D. The authors show how tax incentives increase firms' investment in innovation without being correlated with firms' characteristics. Specifically, Bloom et al. (2013) outline that tax incentives for R&D are uncorrelated with economic or political variables. Hence, tax credit incentives for investment in R&D provide pseudo-random variation to investment in R&D. Since we show that the positive association between creative oriented corporate culture and firm value passes by the investment in R&D, we use tax incentives for R&D to instrument our variable create. Our identification assumption is that tax-credit incentives affect a firm's propensity to undertake innovative projects (i.e. their cultural orientation) without correlating to firm's characteristics. Hence, in a first step, we predict the creation-oriented corporate culture using state dummies and the state level incentives for R&D provided by

[15] The entire database of State-level R&D tax credit can be found on the Wilson website at the following link: http://www.frbsf.org/economic-research/economists/daniel-wilson/

Wilson (2009). The firms’ patenting activity and firms’ value is then regressed on the predicted value of our variable create using time dummies and industry fixed effects plus some control variables. Results are reported in Table 6. Model (1) in Table 6 reports the coefficients estimated using the two stage least squares approach described above. Results show how the coefficients of Create in the two-step regression are significant ($p<0.01$) and larger than in previous models. Specifically, the results reported in Table 6 show that a standard deviation increase in our variable create increase the firm patenting activity by 54.27%. The results reported in Table 6 also show how a standard deviation increase in our variable create increases firm value by 42.67%, representing the 18.68% of our sample average. Therefore, the results from the two-stage model confirm our research hypothesis that a creativity-oriented corporate culture is positively associated with firms’ patenting activity and with firm value.

<< INSERT TABLE 6 >>

7. Conclusions

The majority of firms listed in S&P 500 mention that their innovative capacity largely hinges on their corporate culture. In spite of this, academic literature has ignored the role of corporate culture in the innovation process. This paper provides a first step on this issue. We show that firms that are more oriented to creation invest more in innovation. We also show that this higher investment is associated with higher success in innovation activity. Moreover, we show that a higher success in innovation is positively associated with higher firm value as expressed by Tobin’s Q.

This result outlines that innovation process is associated with firms’ corporate culture. This positive association with firms’ value also explains why firms are strongly focused on advertising innovation among their corporate values.

The reported results complement the findings of Fiordelisi and Ricci (2014), according to which a creativity-oriented corporate culture increases the probability of CEO turnover. Since the findings of this paper show that creativity-oriented companies are more involved in risky innovative projects, it seems plausible to conclude that executives working in companies with such culture orientation are more likely to be fired. This is consistent with recent literature (Aghion et al. 2013) outlining that executives with carrier concerns a là Holmstom (1982) may restrain from innovative projects, as innovation can increase the probability of being fired. This evidence is also consistent with existing literature (Galasso et al., 2011, and Hirshleifer et al., 2012), which indicates that overconfident executives underestimating the risk taken tend to be better innovators.

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Figure 1: Competing Value Framework (CVD)

Panel A:

Flexibility and discretion

Clan
Thrust: Collaborate
Means: Cohesion, participation, communication
Ends: Morale, development commitment

Adhocracy
Thrust: Create
Means: Adaptability, agility, flexibility
Ends: cutting-edge output

Internal focus

External Focus

Nation
Thrust: Control
Means: Capable process, consistency, measurement
Ends: Efficiency, timelines, smooth functioning

Market
Thrust: Compete
Means: Customer focus, productivity, enhancing competitiveness
Ends: Market share, profitability, goal achievement

Stability and Control

Panel B:

Culture	**Assumptions**	**Beliefs**	**Values**	**Artefacts**	**Effectiveness Criteria**
Collaborative (Clan)	Human Affiliation	People behave appropriately when they trust in loyalty to, and membership in the organization.	Attachment, affiliation, collaboration, trust and support	Teamwork, participation, employee involvement and open culture	Employee, satisfaction and commitment
Creative (Adhocracy)	Change	People behave appropriately when they understand the importance and impact of a task.	Growth, stimulation, autonomy and attention to detail	Risk-taking, creativity and adaptability	Innovation
Competitive (Market)	Achievement	People behave appropriately when they have clear objectives and are rewarded based on achievements	Communication, Competition, competence and achievement	Gathering customer information, goal setting, planning, task focus, competitiveness and aggressiveness	Increased market share, profit, product quality and productivity
Control-driven	Stability	People behave appropriately	Communication, reutilisation,	Conformity and predictability	Efficiency timelines and

(Hierarchy)	when they have clear roles, and procedures are formally defined by rules and regulation	formalization and consistency	smooth functioning

Competing Value Framework (CVD)
Panel C:

Culture Type	***Bag of words***
Control	administrat*, analys*, boss*, burocr*, cautio*, cheap*, chief*, conservat*, consisten*, control*, cost*, cut*, disciplin*, document*, effectiv*, efficien*, enhance*, improv*, logic*, measur*, method*, organize*, outcom*, predictab*, procedur*, process*, productiv*, qualit*, regular*, rule*, standard*, system*, technical*, uniform*
Compete	achiev*, acquir*, acquis*, aggress*, analyst*, attack*, client*, challeng*, compet*, customer*, edge*, excellen*, expand*, expans*, fast*, growth*, market*, perform*, position*, pressur*, profit*, rapid*, result*, revenue*, share*, short-term*, speed*, superior*, value*, win*
Collaborate	balan*, capab*, cohes*, collab*, collectiv*, commit*, commun*, competen*, consens*, contribut*, cooperat*, coordin*, decentr*, dialogue*, employ*, empower*, engag*, facilitator*, help*, hir*, human*, interper*, involv*, long-last*, long-term*, loyal*, mentor*, mutual*, people*, relation*, responsib*, retain*, reten*, reward*, skill*, social*, solidif*, team*, teamwork*, train*, willingness*, work group*
Create	adapt*, chang*, creat*, discontin*, dream*, dynamic*, emerg*, entrepre*, envis*, experim*, fantas*, freedom*, futuri*, idea*, imagin*, inventive*, new*, niche*, origin*, pioneer* uncertain*, unpredictable*, ventur*, vision*, unafra*

Table 1:
Variable Description

This table reports the variable description and data sources.

Dependent Variables	Description	Database
$\frac{R\&D\ expenses}{Total\ Assets}$	The ratio of the expenses for research and development in terms of total assets (in %)	Compustat
$Tobin's\ Q_{ijt}$	Total assets minus shareholder equity plus market capitalization divided by total assets	Compustat/CRSP
$\ln(1+pat)_{ijt}$	The natural logarithm of one plus the number of patents applied for during the year	NBER
$\ln(1+cit)_{ijt}$	The natural logarithm of one plus the weighted number of citations received by all the patents granted to a firm by newer patents.	NBER

Cultural Variables	Description	Database
$Create_{ijt}$	The relative frequency of words in the 10-K associated with a creativity-oriented cultural dimension	Edgar
$Collaborate_{ijt}$	The relative frequency of words in the 10-K associated with a collaboration-oriented cultural dimension	Edgar
$Compete_{ijt}$	The relative frequency of words in the 10-K associated with a competition-oriented cultural dimension	Edgar
$Control_{ijt}$	The relative frequency of words in the 10-K associated with a control-oriented cultural dimension	Edgar

Control Variables	Description	Database
$\ln(sales)_{ijt}$	Natural logarithm of total sales	Compustat
$\frac{PPE}{Employees_{ijt}}$	Net Property Plant and Equipment per Employee	Compustat
$Return_{ijt}$	The buy and hold return over the fiscal year	CRSP
$Firm\ age_{ijt}$	Current fiscal year minus first year the firm appears in Compustat	Compustat

$Longholder_{ijt}$	This dummy variable equals 1 if the CEO does not exercise his stock options with a moneyness higher than 67%	Execucomp
$Institutional\ Ownership_{ijt}$	Percentage of equity owned by institutional investors	Thomson Reuters

Table 2
Descriptive Statistics
This Table reports the summary statistics of all variables.

Dependent Variables	Observations	Mean	Standard Deviation
$\frac{R\&D\ expenses}{Total\ Assets}_{ijt}$	4,976	4.3194	6.1087
$Tobin's\ Q_{ijt}$	3,957	2.2835	1.6243
$\ln(1+pat)_{ijt}$	4,976	1.4499	1.6872
$\ln(1+cit)_{ijt}$	4,976	2.3504	2.7610
Cultural Variables	**Observations**	**Mean**	**Standard Deviation**
$Create_{ijt}$	4,976	0.6985	0.2445
$Collaborate_{ijt}$	4,976	1.0076	0.2916
$Compete_{ijt}$	4,976	3.5801	1.0459
$Control_{ijt}$	4,976	2.0414	0.6414
Control Variables	**Observations**	**Mean**	**Standard Deviation**
$\ln(sales)_{ijt}$	4,976	7.0266	1.5828
$\frac{PPE}{Employees}_{ijt}$	4,976	3.8912	1.0862
$Return_{ijt}$	4,976	1.1245	0.5686
$Firm\ age_{ijt}$	4,976	20.5472	12.2498
$Longholder_{ijt}$	4,976	0.4650	0.4988
$Institutional\ Ownership_{ijt}$	4,976	0.4677	0.3320

Table 3
Correlation between corporate culture scores.
This table reports the Pearson correlations between our corporate culture measures and their statistical significance. The corporate culture variables are estimated using text analysis on the firms'10-Ks.

	$Create_{ijt}$	$Collaborate_{ijt}$	$Compete_{ijt}$	$Control_{ijt}$
$Create_{ijt}$	1			
$Collaborate_{ijt}$	0.0548*** (0.0007)	1		
$Compete_{ijt}$	0.2787*** (0.0000)	0.2022*** (0.0000)	1	
$Control_{ijt}$	0.1556*** (0.0000)	0.1291*** (0.0000)	0.3294*** (0.0000)	1

*** p<0.01, ** p<0.05, * p<0.1

Table 4:
R&D Investment

This table relates the expenses for research and development (R&D) on total assets (%), the number of patents applied for by each firm and the patent citations received by the patents owned by each firm (the dependent variables) to our cultural variables Collaborate, Compete, Control, and Create. The latter are constructed by means of text analysis from the firms' 10-Ks. All variables are winsorized at 1% level, centred on their mean and divided by their standard deviation. The regressions include time fixed effects and, where indicated firm or industry fixed effects, the standard errors (reported in parentheses) are clustered at industry level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	$\frac{R\&D\ expenses}{Total\ Assets}$	$\ln(1+pat)$	$\ln(1+cit)$	$\frac{R\&D\ expenses}{Total\ Assets}$	$\ln(1+pat)$	$\ln(1+cit)$	$\ln(1+pat)$	$\ln(1+cit)$
$\frac{R\&D\ expenses}{Total\ Assets}$					0.00096	0.12446***	0.33050***	0.53002***
					(0.02528)	(0.04371)	(0.07199)	(0.09449)
$Create_{ijt-1}$	0.18773*	0.03953**	0.07139*	0.21412**	0.04609**	0.07908*	0.12308***	0.14495**
	(0.11047)	(0.01829)	(0.04258)	(0.09797)	(0.02101)	(0.04178)	(0.03843)	(0.05736)
$Collaborate_{ijt-}$				-0.02915	0.01404	-0.02872	0.05980	0.03051
				(0.05508)	(0.02653)	(0.05904)	(0.03586)	(0.05782)
$Compete_{ijt-1}$				-0.24379***	-0.02683	-0.10423**	-0.05193	-0.07575
				(0.08154)	(0.01945)	(0.04982)	(0.03589)	(0.06111)
$Control_{ijt-1}$				0.28175***	0.02490	0.17514***	0.05415	0.14050**
				(0.10361)	(0.02436)	(0.05817)	(0.03544)	(0.07060)
$\ln(sales)_{ijt-1}$				-0.36443	0.28690***	0.59020***	0.95965***	1.26101***
				(0.36674)	(0.08339)	(0.14032)	(0.05672)	(0.08089)
$\frac{PPE}{Employees}_{ijt-1}$				-0.14426	0.15180**	0.24520*	0.34101***	0.46540***
				(0.24441)	(0.07531)	(0.14341)	(0.11162)	(0.14206)
$Return_{ijt-1}$				-0.18775***	0.00062	0.02942**	0.04245***	0.07664***
				(0.04692)	(0.00699)	(0.01403)	(0.00969)	(0.02096)
$Firm\ age_{ijt-1}$				0.15144**	0.04495*	0.05167	0.00534	0.00781
				(0.07192)	(0.02669)	(0.04263)	(0.00358)	(0.00559)
$Longholder_{ijt-}$				-0.13594*	0.07039**	0.19696***	0.11099**	0.23030***
				(0.07757)	(0.02859)	(0.05217)	(0.04486)	(0.07955)
$Institutional\ Ownership_{ijt-1}$				-0.11174	0.00761	-0.00809	0.04627	0.08942
				(0.15353)	(0.03714)	(0.07868)	(0.03701)	(0.07585)
$Constant$	4.62157***	1.57543***	3.14159***	2.13582*	0.92594**	2.37149***	1.63464***	3.15208***
	(0.13556)	(0.04474)	(0.08802)	(1.23000)	(0.43223)	(0.69068)	(0.09559)	(0.14986)
$Time\ fixed\ eff$	Y	Y	Y	Y	Y	Y	Y	Y
$Firm\ fixed\ eff$	Y	Y	Y	Y	Y	Y	N	N
$Industry\ fixed$	N	N	N	N	N	N	Y	Y
$Observations$	4,976	4,976	4,976	4,976	4,976	4,976	4,976	4,976

*** p<0.01, ** p<0.05, * p<0.1

Table 5:
Firm Value

This table shows the results of the relation between the dependent variable Tobin's Q, and corporate culture, as measured by Collaborate, Compete, Control and Create which are constructed using textual analysis from the companies' 10-Ks. All variables are winsorized at 1% level, centred on their mean and divided by their standard deviation. We control in each model for time fixed effects and as specified by firm or industry fixed effects. The standard errors are reported in parentheses and are clustered at industry level.

	(1) $Tobin's\ Q$	(2) $Tobin's\ Q$	(3) $Tobin's\ Q$	(4) $Tobin's\ Q$
$\frac{R\&D\ expenses}{Total\ Assets}$		0.34811**	0.31623***	0.34256***
		(0.13627)	(0.10533)	(0.11272)
$Create_{ijt-1}$	0.10030**	0.09027*	0.06227*	0.02792
	(0.04562)	(0.04567)	(0.03610)	(0.05926)
$Collaborate_{ijt-1}$			-0.10153*	-0.07550
			(0.05295)	(0.04552)
$Compete_{ijt-1}$			-0.00936	-0.05618
			(0.02455)	(0.04354)
$Control_{ijt-1}$			0.14791***	0.00788
			(0.05411)	(0.04326)
$\ln(sales)_{ijt-1}$			-0.97130***	0.05863
			(0.22323)	(0.03920)
$\frac{PPE}{Employees}_{ijt-1}$			-0.21028	0.18819*
			(0.16054)	(0.10470)
$Return_{ijt-1}$			0.11038***	0.12796***
			(0.02767)	(0.03205)
$Firm\ age_{ijt-1}$			-0.00313	-0.00645
			(0.01046)	(0.00575)
$Longholder_{ijt-1}$			0.30525***	0.63304***
			(0.04015)	(0.08636)
$Institutional\ Ownership_{ijt-1}$			-0.06150	0.08437
			(0.06584)	(0.05417)
$Constant$	2.30126***	2.16444***	1.82426***	1.89466***
	(0.06936)	(0.10324)	(0.16953)	(0.17522)
$Time\ fixed\ effects$	Y	Y	Y	Y
$Firm\ fixed\ effects$	Y	Y	Y	N
$Industry\ fixed\ effects$	N	N	N	Y
$Observations$	3,957	3,957	3,957	3,957

*** p<0.01, ** p<0.05, * p<0.1

Table 6
Instrumenting creative corporate culture with tax credit on R&D

This table relates the number of patents applied for by each firm, the patent citations received by the patents owned by each firm and firm value (Tobin's Q) (the dependent variables) to our cultural variable Create. The latter is constructed by means of text analysis from the firms' 10-Ks. In the models reported below the cultural variable create is instrumented with the changes in the tax credits for R&D at a state level as reported in Wilson (2009). The first stage F-statistic is also reported. All variables are winsorized at 1% level centred on their means and divided by their standard deviation. The regressions include time fixed effects and industry fixed effects; the standard errors (reported in parentheses) are robust to arbitrary heteroskedasticity and allow for first order autocorrelation.

	(1)	(2)	(3)
	$\ln(1+pat)$	$\ln(1+cit)$	$Tobin's\ Q$
$Create_{ijt-1}$	0.54278***	0.71287***	0.42671***
	(0.11505)	(0.18167)	(0.11576)
$\ln(sales)_{ijt-1}$	0.81044***	1.05097***	-0.12194***
	(0.03240)	(0.04938)	(0.03952)
$\frac{PPE}{Employees}_{ijt-1}$	0.22834***	0.31506***	0.11188**
	(0.04487)	(0.07211)	(0.04971)
$Return_{ijt-1}$	0.00445*	0.00512	-0.00588**
	(0.00232)	(0.00361)	(0.00246)
$Firm\ age_{ijt-1}$	0.03590**	0.07126**	0.13255***
	(0.01690)	(0.02880)	(0.03122)
$Longholder_{ijt-1}$	0.11448***	0.23069***	0.76789***
	(0.04322)	(0.06981)	(0.05327)
$Institutional\ Ownership_{ijt-1}$	0.06330**	0.11504***	0.10090***
	(0.02535)	(0.04059)	(0.03293)
$Constant$	1.11763***	0.35178	0.57262***
	(0.37315)	(0.54333)	(0.12612)
$Time\ fixed\ effects$	Y	Y	Y
$Industry\ fixed\ effects$	Y	Y	Y
$Observations$	4,942	4,942	3,923
First stage F-statistic	7.194	7.194	7.203

*** p<0.01, ** p<0.05, * p<0.1